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ABSTRACT

Value investing delivers volatile returns, with large drawdowns during both market booms and busts. This paper interprets these returns through an intertemporal CAPM, which predicts that aggregate cash flow, discount rate, and volatility news all move value returns. We document that indeed these shocks explain a large fraction of quarterly value returns over the last 60 years. We also distinguish between the intra-industry and inter-industry components of value, showing that the ICAPM explains the former better. Finally, we develop a novel methodology to perform this decomposition at the daily frequency, using it to interpret value returns during the Covid-19 pandemic.

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A data appendix is available at http://www.nber.org/data-appendix/w31859

1 Introduction

Value investors seek to buy stocks that are cheap in the sense that their market prices are low relative to accounting measures of their value. This investment approach has a long history predating modern finance theory (see for example Graham, Dodd, and Cottle 1934). A value strategy can be implemented using various alternative valuation ratios such as the dividend yield, earnings-price ratio, or book-market ratio, but since the influential work of Fama and French (1992, 1993) academic research on value has primarily emphasized the book-market ratio.[2]

If a value strategy uses an accounting measure of a stock's value that captures its rationally expected future cash flows, discounted at a constant rate, then by the logic of Campbell and Shiller (1988a), the corresponding valuation ratio should be a good proxy for the rationally expected long-run return on the stock. This insight implies that a value portfolio should contain stocks with high average returns, either because they are risky stocks with high equilibrium returns, or because they are stocks that have been underpriced by irrational investors.

Whether value returns are high on average or not, they are very far from riskless. Figure 1 illustrates this by plotting the return to the standard Fama-French long-short value strategy, HML, over the period 1963Q1–2022Q1. The raw quarterly log return to HML is smoothed for readability using an exponentially weighted moving average with a half-life of two years. The solid black line in the figure shows large swings in HML returns, with value booms in the late 1970s, mid 1980s, and mid 2000s, and short but sharp value busts in the early 1970s, the early 1980s, the early 1990s, the turn of the millennium, the global financial crisis of 2008-09, and—most striking of all—the Covid-19 pandemic of 2020-21.

This paper asks what factors drive such booms and busts in value. We make two preliminary observations. First, value booms and busts do not line up with returns on the aggregate stock market. Figure 1 illustrates this by plotting the log real return on the CRSP value-weighted index, smoothed in the same way as the HML return, as a dashed red

[2]Early academic papers on value investing using the dividend yield as a valuation ratio include Litzenberger and Ramaswamy (1982) and Miller and Scholes (1982). Basu (1977, 1983) uses the earnings-price ratio, and Stattman (1980) and Rosenberg, Reid, and Lanstein (1985) use the book-market ratio. Goncalves and Leonard (2023) propose an alternative way to estimate the fundamental value of a company, that may obviate a potential deterioration of book equity as a measure of fundamental value. See also earlier work by Frankel and Lee (1998) as well as Cong, George, and Wang (2023).

line. The earlier value busts coincide with high aggregate stock returns, but value busts in the global financial crisis and the Covid-19 pandemic coincide with sharp declines in the aggregate market. Overall, there is little correlation between the two lines in Figure 1, consistent with the fact that HML has a negative beta with the aggregate market that is close to zero in absolute value.

Second, value booms and busts primarily result from returns to value within industries. We create an intra-industry value strategy that holds stocks whose book-market ratios are high relative to other stocks in the same industry.[3] We regress HML onto the return of this strategy and call the fitted value intra-industry HML, or $\mathrm{HML}_{\mathrm{Intra}}$, and the residual inter-industry HML, or $\mathrm{HML}_{\mathrm{Inter}}$. With this procedure, HML is the sum of the two components and inter-industry HML picks up industry shocks that are orthogonal to intra-industry value returns. Figure 2 plots the log returns to HML and its two components over the same sample period and using the same smoothing procedure as Figure 1. The importance of intra-industry HML, the dashed green line in the figure, is immediately visible. However, many value busts do coincide with poor returns to inter-industry HML, the dash-dotted red line, despite the zero unconditional correlation (by construction) between intra-industry and inter-industry HML.

If booms and busts in value are not explained by aggregate stock returns, are there other aggregate shocks that do explain them? In this paper we argue that three factors derived from data on the aggregate stock market go a long way to explain the volatile history of value returns, both to HML itself and particularly to its intra-industry component.

We measure the aggregate shocks that are relevant for value investors using an intertemporal CAPM (Merton 1973). Specifically, we follow Campbell and Vuolteenaho (CV 2004) in distinguishing market cash-flow news (upward revisions in rationally expected market dividends, discounted to the infinite future at a constant rate) and negative discount-rate news (downward revisions in rationally expected market returns, again discounted to the in-

[3]We are not the first to decompose value into intra- and inter-industry components. Cohen, Polk, and Vuolteenaho (2003) provide a variance decomposition of firm-level BE/ME and find "that the book-to-market effect in returns is mostly an intra-industry effect." Other papers include Cohen and Polk (1998) (the first to study intra- and inter-industry value strategies), Lewellen (1999), and Asness, Porter, and Stevens (2000). Daniel, Grinblatt, Titman, and Wermers (1997) use Cohen and Polk's (1998) adjustment in their popular characteristic-based approach to performance evaluation. Industry-adjustment is widely-used in practice; see, for example, Israel, Jiang, and Ross (2018), who argue that careful industry adjustment of value characteristics is an example of "craftsmanship alpha" that skilled fund managers can provide.

finite future at a constant rate). The total return on the market equals cash-flow news plus negative discount-rate news, and so a stock's covariance with the market can be expressed as its covariance with cash-flow news plus its covariance with negative discount-rate news. Dividing these covariances by the variance of the return on the market, a stock's beta with the market can be written as the sum of its cash-flow and discount-rate betas.

In a homoskedastic setting, CV show that conservative long-term investors charge a different risk price for exposure to these two types of aggregate shocks, with cash-flow beta ("bad beta") commanding a higher price than discount-rate beta ("good beta"). CV further show that value stocks have higher cash-flow betas but lower discount-rate betas and overall market betas than growth stocks. This pattern may reflect the lower duration of value stocks, whose cash flows are concentrated in the near term, relative to growth stocks.[4] According to the CV model, value stocks are likely to underperform in a period when the aggregate market is driven down by bad cash flow news, but also in a period when the market is driven up by declining discount rates. There need be no strong unconditional relationship between value returns and aggregate stock returns since both types of shocks affect the aggregate market.

Campbell, Giglio, Polk, and Turley (CGPT 2018) extend the CV model to include shocks to the variance of stock returns. Using a model in which the market return and all predictor variables share a common process for volatility, CGPT show that long-run market volatility shocks (upward revisions in the rationally expected value of future market return variances, discounted to the infinite future at a constant rate) are relevant to long-term investors because they alter the quality of investment opportunities. Conservative long-term investors charge a risk price for exposure to volatility shocks that depends on the volatility process and risk aversion, but not on any other preference parameters. CGPT find that value stocks have lower volatility betas than growth stocks, perhaps reflecting the optionality of growth-company investment opportunities that increases the prices of growth stocks in an uncertain environment. According to the CGPT model, a period with unusual upward shocks to volatility is likely to be a period in which value underperforms.

In this paper, we estimate the VAR model specified by CGPT, using quarterly data from 1926Q3 through 2022Q1. The model generates quarterly news shocks similar to those

[4] A recent literature stresses this duration effect. See Dechow, Sloan, and Soliman (2004), Lettau and Wachter (2007), Weber (2018), and Gormsen and Lazarus (2021).

estimated in CV and CGPT.[5] In the period since 1963Q3 where the return to value is anomalously high relative to its market beta (the "modern period" studied by CV and CGPT), we estimate the betas of HML and its intra-industry and inter-industry components with the three shocks to cash flows, discount rates, and volatility. We find similar betas for HML to those reported in prior research. A novel result is that intra-industry HML has a considerably higher cash-flow beta and considerably lower volatility beta than inter-industry HML. Since cash-flow and volatility betas are highly compensated in the ICAPM, this pattern helps to explain the higher average return to intra-industry HML than to inter-industry HML.

Over our full sample period since 1963Q3, the three ICAPM shocks explain almost half (48%) of the variance of HML, 39% of the variance of intra-industry HML, but only 13% of the variance of inter-industry HML. In a more recent sample period starting in 1990 (a period in which we can also perform the analysis at a higher frequency, as described below), the explanatory power of the ICAPM is again 48% for HML and increases to 43% for intra-industry HML. The ICAPM fit also improves for inter-industry HML in this period but remains modest at 18%. These statistics suggest that the pattern of ICAPM shocks has the potential to explain recent value returns and particularly the returns to intra-industry HML.

Our ICAPM shocks provide more than just a statistical fit to HML's fluctuations: they also help us understand the main economic drivers of HML returns. Our analysis identifies what news was most important at different times, highlighting that different periods see different mixes of the news shocks moving HML. There are periods when different news shocks have offsetting effects on HML (for example the 1970s, with cash-flow news offsetting discount rate news and variance news), and other periods when all news terms move HML in the same direction (for example the technology boom in the late 1990s).

One particularly interesting event is the Covid-19 pandemic. During the pandemic, all three types of news arrived at a rapid pace and market returns were unusually volatile. These facts meant that major shocks occurred at a higher frequency than quarterly. To

[5] Our approach uses the CGPT unrestricted VAR to measure the three shocks driving value returns. In contrast, the structured approach of Campbell, Giglio, and Polk (2013) imposes the cross-sectional restrictions of the two-beta CV ICAPM when estimating the time-series VAR to sharpen equity premium forecasts and the resulting decomposition of unexpected market returns into discount-rate and cash-flow news. Given our focus on the time-series decomposition of returns (as opposed to the cross-sectional fit of the model), in this paper we estimate the VAR from the time-series information alone, as in CGPT.

understand the returns to value in 2020, we adapt the CGPT framework and estimate a daily VAR. We start our sample period at the beginning of 1990 and end at the end of 2022Q1. Focusing on this sub-period allows us to include the VIX as an additional state variable relevant for predicting future volatility. We show that the daily version of the ICAPM gives a good account of HML and intra-industry HML returns throughout this sub-period and specifically in 2020. The high-frequency variation of returns in 2020 is primarily driven by cash-flow news, because volatility and discount-rate news had largely offsetting effects on HML and intra-industry HML.

While the ICAPM helps us to understand the returns to intra-industry HML, it has much lower explanatory power for inter-industry HML. To gain some insight into value returns across industries, we measure earnings growth shocks to value industries relative to growth industries. We show that the Covid-19 pandemic particularly hurt the earnings of value industries, which tend to be physical businesses, relative to growth industries. This sectoral shock, rather than an aggregate shock, is the main explanation for the drawdown of inter-industry HML in 2020.

We conclude this introduction with a caveat. Our paper is about the time-series variability of value returns and not about gradual shifts in the average return to value. Many commentators have noted that the average return to HML has been lower in recent decades, and particularly since the global financial crisis in 2008, than it was in the earlier part of our sample period. This fact is clearly visible in Figure 1, and Figure 2 shows that it primarily reflects a lower average return to intra-industry value. It is not clear whether this phenomenon reflects a structural shift or simply a sequence of unfavorable shocks to value stocks, and we do not seek to resolve this issue here.[6]

The organization of the paper is as follows. Section 2 sets up a quarterly VAR model and explains how we estimate the three aggregate ICAPM shocks to market cash flows, market discount rates, and market variance. Section 3 estimates the betas of HML and its two components with these three shocks, and studies the time-series evolution of the ICAPM-predicted returns to HML, intra-industry HML, and inter-industry HML at a quarterly frequency. Section 4 sets up a daily model and reestimates the ICAPM shocks at a daily

[6]For example, Fama and French (2020) are unable to reject the hypothesis that the value premium is the same in both halves of the July 1963 - June 2019 sample. However, if they forecast the value premium using Cohen, Polk, and Vuolteenaho's (2003) value spread, they do find some evidence of a second-half decline in the expected value premium.

frequency. The daily ICAPM is then applied to understand the returns to HML and its two components during the Covid-19 pandemic. Section 5 studies the cross-sectional pattern of industry earnings shocks in 2020 and argues that this pattern contributed to the poor performance of inter-industry HML at that time. Section 6 concludes. An online appendix (Campbell, Giglio, and Polk 2023) provides additional supporting evidence.

2 A Quarterly VAR Model for Aggregate Stock Returns and Volatility

2.1 News terms and the dynamics of the economy

In this paper, we build on CGPT (2018) to describe the dynamics of the economy. Like them, we assume that the economy is well described by the following first-order vector autoregression (VAR):

$$\mathbf{x}_{t+1} = \bar{\mathbf{x}} + \mathbf{\Gamma}\left(\mathbf{x}_t - \bar{\mathbf{x}}\right) + \sigma_t \mathbf{u}_{t+1}, \tag{1}$$

where $\mathbf{x}_t$ is an $n \times 1$ vector of state variables which includes the market return r_t as its first element, $\bar{\mathbf{x}}$ and $\mathbf{\Gamma}$ are an $n \times 1$ vector and an $n \times n$ matrix of constant parameters, and $\mathbf{u}_{t+1}$ is a vector of shocks to the state variables normalized so that its first element has unit variance. As in CGPT, we assume that $\mathbf{u}_{t+1}$ has a constant variance-covariance matrix $\mathbf{\Sigma}$, with element $\Sigma_{11} = 1$, and include σ_t^2, the variance of returns, in the state vector as the second element. We define $n \times 1$ vectors $\mathbf{e}_1$ and $\mathbf{e}_2$, all of whose elements are zero except for a unit first element in $\mathbf{e}_1$ and a unit second element in $\mathbf{e}_2$. Finally, whereas $\mathbf{u}_{t+1}$ refers to the scaled VAR innovations (i.e., normalized by σ_t), we refer to $\eta_{\mathbf{t+1}}$ as the raw, or unscaled, VAR innovations: $\eta_{\mathbf{t+1}} = \sigma_t \mathbf{u}_{t+1}$.

CGPT derive the first-order conditions of a long-term investor with Epstein-Zin utility that is holding the market in equilibrium. The paper shows that equilibrium pricing from these first order conditions (i.e., the stochastic discount factor associated with this investor's Euler equation) involves three priced shocks: to (aggregate) cash flow news, discount rates, and variance. These news terms can be expressed as a function of the VAR parameters:

$$N_{DR,t+1} = \underbrace{\mathbf{e}_1' \rho \mathbf{\Gamma} \left(\mathbf{I} - \rho \mathbf{\Gamma}\right)^{-1}}_{\lambda_{DR}} \eta_{t+1}, \tag{2}$$

$$N_{CF,t+1} = \underbrace{\left(\mathbf{e}_1' + \mathbf{e}_1'\rho\boldsymbol{\Gamma}(\mathbf{I} - \rho\boldsymbol{\Gamma})^{-1}\right)}_{\lambda_{CF}} \eta_{t+1}, \tag{3}$$

$$N_{V,t+1} = \underbrace{\rho\mathbf{e}_2' \left(\mathbf{I} - \rho\boldsymbol{\Gamma}\right)^{-1}}_{\lambda_V} \eta_{t+1}, \tag{4}$$

which we refer to as discount rate news, cash flow news, and variance news respectively. The parameter ρ is the loglinearization parameter of the Campbell-Shiller approximation, and should be thought of as close to one (we follow CGPT and use 0.95 in our empirical work). Each news term loads linearly on the innovations η_{t+1}, and we refer to the loadings as λ_{DR}, λ_{CF}, and λ_V respectively.

In CGPT's model, the risk premium that an asset yields depends on its exposure to these three news terms. While that paper focuses on the cross-sectional implications of the model, in this paper we investigate the *time-series* relation between the returns of the value (HML) portfolio and the realizations of these news shocks. That is, we investigate to what extent the fluctuations in HML can be explained by its exposure to these three aggregate shocks.

We begin in the next section by estimating the VAR parameters and studying the time series of the news terms. After that, we relate these estimated news terms to the returns of HML.

2.2 VAR specification

To implement the VAR estimation, we need to choose the variables that are included in the state vector. We use the same six state variables as in CGPT (2018), with one exception: we replace their interest rate variable with the term yield spread.[7] The data are quarterly, from 1926Q3 to 2022Q1. Given that the VAR is used to extract news about cash flows, discount rates, and volatility for long horizons, and contains very persistent variables, using this long sample is important to obtain precise estimates of the dynamics. In fact, CGPT show that this VAR specification is a good forecaster of stock return variance at very long horizons.

The first variable in the VAR is the log real return on the market, r_M, the difference between the log return on the Center for Research in Securities Prices (CRSP) value-weighted

[7]The published version of CGPT uses the 3-month Treasury bill yield, but we follow CV, Campbell, Giglio, and Polk (2013), and the NBER working paper version of CGPT and use the term yield spread instead. All our conclusions are robust to using the 3-month bill yield in place of the term yield spread.

stock index and the log return on the Consumer Price Index. This portfolio is a standard proxy for the aggregate wealth portfolio, but CGPT confirm the robustness of their findings to alternative proxies that delever the market return by combining it in various proportions with Treasury bills. The second variable is expected market variance ($EVAR$). This variable is meant to capture the variance of market returns, σ_t^2, conditional on information available at time t, so that innovations to this variable can be mapped to the N_V term described above.

To construct $EVAR_t$, we proceed as follows. We first construct a series of within-quarter *realized* variance of daily returns for each time t, $RVAR_t$. We then run a regression of $RVAR_{t+1}$ on lagged realized variance ($RVAR_t$) as well as the other five state variables at time t. This regression then generates a series of predicted values for $RVAR$ at each time $t+1$, that depend on information available at time t: $\widehat{RVAR}_{t+1}$. Finally, we define our expected variance at time t to be exactly this predicted value at $t+1$:

$$EVAR_t \equiv \widehat{RVAR}_{t+1}. \tag{5}$$

Note that though we describe our methodology in a two-step fashion where we first estimate $EVAR$ and then use $EVAR$ in a VAR, this choice is only for interpretability. Indeed, this approach to modeling $EVAR$ can be considered a simple renormalization of equivalent results we would find from a VAR that included $RVAR$ directly.[8]

The third variable is the log of the S&P 500 price-smoothed earnings ratio (PE) adapted from Campbell and Shiller (1988b), where earnings are smoothed over ten years.[9] The fourth is the term yield spread ($TERM$) measured as the difference between the log yield on 10-year Treasuries and the log yield on 3-month Treasuries, obtained from the Federal Reserve Bank of St. Louis. The fifth is the small-stock value spread (VS), constructed as described in CGPT and Campbell, Giglio, and Polk (2013).

The sixth and final variable is the default spread (DEF), defined as the difference between

[8]As discussed in CGPT, observations are weighted based on $RVAR$ in the first stage and then reweighted using $EVAR$ in the second stage, so our two-stage approach in practice is not exactly the same as a one-stage approach. CPGT explore the robustness of their results to several different ways of estimating their VAR, including using a $RVAR$-weighted, single-step estimation approach.

[9]The PE ratio reported on Robert Shiller's website compares a monthly average of daily closing prices to smoothed earnings. To faciliate our use of these data at the daily frequency, we replace Shiller's monthly average price with the relevant closing price at month-end.

the log yield on Moody's BAA and AAA bonds, obtained from the Federal Reserve Bank of St. Louis. We include the default spread in part because that variable is known to track time-series variation in expected real returns on the market portfolio (Fama and French, 1989), but also because shocks to the default spread should to some degree reflect news about aggregate default probabilities, which in turn should reflect news about the market's future cash flows and volatility.[10]

We follow CGPT in estimating our VAR, and refer the reader to that paper for details. Appendix Table 1 reports the estimates of the regression of $RVAR$ onto the lagged variables (used to build EVAR) and the VAR parameter estimates. All the estimates are similar to those in CGPT.

2.3 Estimated news terms

Table 1 presents the standard deviation/correlation matrix of the news terms, estimated by combining the estimated VAR parameters and innovations. The standard deviations are broadly comparable with those reported by CGPT, and the correlations are qualitatively similar. Cash-flow news is positively correlated with negative discount-rate news, implying that positive cash-flow shocks are associated with declines in discount rates that amplify the response of stock prices. Cash-flow news is negatively correlated with variance news, implying that positive cash-flow shocks are associated with reductions in equity market risk. Quantitatively, the correlations we estimate are somewhat larger in absolute value than those reported by CGPT.

Figure 3 plots the three news terms, smoothed for readability using an exponentially-weighted moving average (EWMA) with a half-life of two years. While the news terms are produced for the entire sample starting in 1926 (the sample we use to estimate the VAR), we focus here on the "modern sample" starting in 1963, during which, as shown by Campbell and Vuolteenaho (2004) and CGPT, the cross-section of risk premia is significantly better described by the ICAPM than by the CAPM.

The vertical line in the graph marks the year 1990. As discussed in the introduction, in this paper we pay special attention to the post-1990 period, a period for which we observe

[10]Again, to faciliate our use of these data at the daily frequency, for both the term spread and the default spread, we use the version of the series in question that reflects daily closing yields rather than average yields.

additional variables at the daily frequency, that allow us to increase the frequency of the estimation of the news terms.

The patterns in the figure are consistent with previous research. Most of the variation in aggregate returns comes from discount-rate news as shown in Campbell (1991). Campbell and Vuolteenaho (2004) emphasize how patterns in cash-flow news are distinct from those in discount-rate news, which the figure broadly confirms. Cash-flow news is positive in the 1960s and then is mostly negative during the 1970s and 1980s. The 1990s bring positive cash-flow news which continues throughout the early 2000s until the Global Financial Crisis, a market downturn driven by the arrival of negative cash-flow news. This large negative shock is consistent with Campbell, Giglio, and Polk (2013) who document that in the history of booms and busts in the U.S., the 2007-2009 downturn was one of a few that were driven mainly by cash-flow news. Consistent with the results in CGPT, volatility news spikes during the tech boom and the Global Financial Crisis.

Relative to this previous work, our updated sample includes the Covid-19 episode of 2020, marked by a combination of negative cash flow news, positive volatility news, and positive discount rate news. The figure also shows that the news arriving in early 2020 was quickly reversed over the following quarters. The fast reversal suggests that higher frequency data (which we analyze later in the paper) will be useful to obtain a more complete understanding of the Covid-19 episode.

3 A Quarterly ICAPM Perspective on HML and its Components

In this section we study the time series of returns of HML and explore to what extent they can be explained by exposure to the three aggregate news shocks. To facilitate our interpretation of the exposure of HML to these three news shocks, we decompose Fama and French's (1993) value strategy into an intra-industry and an inter-industry component.

3.1 Decomposing HML

The construction of HML, following Fama and French (1993), involves double-sorting stocks by their market capitalization and their book-to-market ratio. Because different industries include firms of different sizes with different book-to-market ratios, HML generally overweights certain industries relative to others, that is, it is not industry-neutral. For example, banks tend to be value companies, and thus tend to be overweighted in HML. To better understand the drivers of HML returns, we decompose HML into an intra-industry component that has no industry exposure and an inter-industry component that captures the effects of industry tilts on HML. We refer to the first as $\text{HML}_{\text{Intra}}$, and to the second as $\text{HML}_{\text{Inter}}$. The focus on this decomposition is motivated by previous evidence (e.g., Cohen, Polk and Vuolteenaho 2003) that has shown that value is in large part an intra-industry phenomenon. We therefore explore the possibility that the ICAPM news terms might explain the returns to the two components differently.

There are multiple ways to perform this decomposition, some of which have been explored in previous literature. The approach we use builds an HML portfolio separately for each industry (following the same procedure as Fama and French 1993, and using the 48 industries of Fama and French 1997), and then aggregates the returns of the industry-specific HML portfolios by weighting the industries by their market capitalization. This procedure yields a long-short intra-industry HML portfolio which, by construction, has no industry exposure. We next construct the inter-industry component as the residual of a regression of HML onto the intra-industry component. We define $\text{HML}_{\text{Inter}}$ as the residual of this regression. Finally, we construct $\text{HML}_{\text{Intra}}$ as the rescaled intra-industry component, where the scaling is such that a regression of HML onto $\text{HML}_{\text{Intra}}$ has a coefficient of exactly 1. Thanks to this rescaling, we can then write:

$$HML = HML_{Intra} + HML_{Inter}, \tag{6}$$

where the two components are orthogonal.[11]

We begin by describing some of the main features of HML, $\text{HML}_{\text{Intra}}$, and $\text{HML}_{\text{Inter}}$ in the modern sample (1963Q3-2022Q1). The risk premia of the three portfolios are 0.93%, 1.32%, and -0.39% per quarter, respectively. The HML risk premium is positive (and statistically significant with a t-statistic of 2.34) over the modern sample, despite the lower premium

[11] A similar intra-industry HML portfolio is available on Robert Novy-Marx's website at https://rnm.simon.rochester.edu/. We only consider industries for which we have at least one stock in each of the four portfolios used to build HML (large growth, small growth, large value, small value), so that an HML portfolio can be built within that industry.

earned by value over the last 15 years. The HML premium can be entirely attributed to the intra-industry component, whereas the inter-industry component has no significant risk premium (t-statistics of 3.94 and -1.82, respectively).

Table 2 shows how HML, $\text{HML}_{\text{Intra}}$, and $\text{HML}_{\text{Inter}}$ (built using our benchmark specification) relate to each other. The table has three panels, with the first one focusing on the entire modern sample (1963Q3-2022Q1), and the other two panels on the pre-1990Q2 and post-1990Q1 samples, respectively.[12]

Starting from the modern sample (panel A), the first row reports the results of a regression of HML on the intra-industry component. Given the way intra-industry HML is scaled, this regression has by construction a coefficient of 1. The R^2 of the regression is high, close to 70%, indicating that time-series variation in the intra-industry component of HML is closely related to variation in HML. The second row reports the regression of $\text{HML}_{\text{Intra}}$ onto HML (which mechanically has the same R^2). Both regressions show a statistically significant alpha (negative in the first regression and positive in the second regression), which indicates that the intra-industry component of HML commands a risk premium that goes beyond that of HML.

The third row shows that $\text{HML}_{\text{Inter}}$ has a large negative alpha with respect to HML and a much lower correlation with HML than does $\text{HML}_{\text{Intra}}$. Together, these results suggest that the intra-industry component is highly priced by investors, whereas the inter-industry component, i.e., the component of HML that is uncorrelated with $\text{HML}_{\text{Intra}}$, carries a much smaller risk premium.

The last three rows of the panel study the market exposure of the three portfolios. Row (4) shows that HML is weakly negatively related to the market – its beta is -0.17, and the R^2 of the projection onto the market is only 5%. This regression indicates that exposure to the market alone will not be sufficient to understand HML's fluctuations. The same is true for $\text{HML}_{\text{Intra}}$ and $\text{HML}_{\text{Inter}}$; we will need to go beyond the market to understand variation in their returns. Finally, the table also shows that while the intra-industry portfolio is responsible for most of HML's CAPM alpha, the inter-industry portfolio is responsible for most of HML's market beta.

Panels B and C of the table repeat the analysis splitting the sample in 1990. The results highlighted above continue to hold in the two samples, with few exceptions. $\text{HML}_{\text{Intra}}$

[12]We choose this specific split becasue we have a complete quarter of daily news only starting in 1990Q2.

explains most of the alpha *and* the market beta of HML before 1990. In addition, the overall alpha of HML is, as well known, much lower in the recent period. This decrease in HML alpha is mirrored by a decrease in the alpha of $\text{HML}_{\text{Intra}}$.

As we have already discussed, Figure 2 shows the time series of (EWMA-smoothed) log returns on HML and its two components in the modern period. Several of the patterns of Table 2 are visible in the figure. The fluctuations in HML closely match those of $\text{HML}_{\text{Intra}}$, during booms and busts. $\text{HML}_{\text{Inter}}$ instead seems to be less correlated with HML and $\text{HML}_{\text{Intra}}$, though it does tend to experience crashes at the same time (e.g., during the Covid-19 pandemic). In the remainder of this paper, we seek to explain the booms and busts in HML and its two components using the three ICAPM shocks that we have estimated.

3.2 HML and the ICAPM news terms

We next study how HML loads on the aggregate news terms estimated from the VAR. We also explore how the two components, $\text{HML}_{\text{Intra}}$ and $\text{HML}_{\text{Inter}}$, load on them: to the extent that the two components load differentially on these news terms, this analysis can provide an interesting new test of CGPT's neoclassical explanation for the value effect and can also facilitate a deeper understanding of the sources of HML's fluctuations.

Table 3 shows the three portfolios' market betas, as well as their betas with respect to the ICAPM news terms plotted in Figure 2.[13] The table reports univariate betas on the left side, and multivariate betas on the right side.[14] We begin from the top panel, that uses the entire modern sample. As highlighted in Table 2, we find that HML has a negative market beta, confirming the findings of CV and CGPT. HML's negative CAPM beta comes from the strategy's negative discount-rate beta, which masks a positive cash-flow beta. In addition, HML has a negative variance beta. These findings continue to hold in a multiple regression context.

The last column of the table reports the R^2 of the multiple regression. Strikingly, the ICAPM news terms explain nearly 50% of the time-series variation in HML, a dramatic

[13]Note that Table 2 estimates market betas using simple excess returns on the market while Table 3 estimates betas using the unexpected component of log real market returns. Thus, the estimates should not be exactly equal to each other.

[14]When reporting the results of the simple and multiple regressions, we follow CV and CGPT and measure ICAPM betas by scaling the covariance of value returns with each ICAPM shock by the total variance of unexpected market returns, not by the variance of the particular shock in question.

increase from the mere 5% explained by the market factor (see Table 2). This result is important because it tells us that the ICAPM news terms are not only useful in explaining the cross-section of risk premia (as demonstrated by CGPT), they are also helpful in explaining period-by-period fluctuations in value returns, and therefore they can be useful in interpreting the (proximate) sources of HML's booms and busts.

Of course, this explanatory power is in part due to the inclusion of the value spread in the VAR, and shocks to the value spread should be negatively correlated with the return on HML. Indeed, a regression of HML on the value spread shock has an R^2 of 52%. However, it is important to recognize that the value spread shock is combined with all of the other five shocks driving the VAR when computing the ICAPM news terms (via the λ vectors). Moreover, the λ vectors are not optimized to describe the cross-section of average returns or to explain the realized returns on HML. Instead, they are chosen based on the ability of the variables in the VAR, such as the value spread, to forecast future aggregate returns and risks, as well as on the dynamics of the state variables, as the economic logic of the ICAPM explicitly requires.

The next two rows of the table focus on the intra- and inter-industry components of HML. They reveal several novel facts about value and the intertemporal CAPM. First, $\text{HML}_{\text{Inter}}$ is responsible for a significant proportion of HML's discount-rate beta (and, as noted above, of HML's market beta). However, almost all of HML's cash-flow beta comes from the $\text{HML}_{\text{Intra}}$ component, which is also responsible for almost all of the variance beta of HML. $\text{HML}_{\text{Inter}}$, instead, has essentially zero cash-flow and variance beta. These facts are broadly consistent with the differences in average returns on these two components of HML. The component of value contributing to HML's CAPM alpha is also the component that provides the lion's share of exposure to the two ICAPM betas that command relatively large risk prices. The component of value that does not contribute to HML's CAPM alpha is also the component that is mostly sensitive to the temporary component of aggregate returns, which carries the smallest risk price in the ICAPM.

The ability of the ICAPM to explain the fluctuations of these portfolios is also markedly different between $\text{HML}_{\text{Intra}}$ and $\text{HML}_{\text{Inter}}$. While the ICAPM has the highest (time-series) explanatory power for HML, it has similar power for $\text{HML}_{\text{Intra}}$, but performs significantly worse in explaining the fluctuations of $\text{HML}_{\text{Inter}}$. This difference in explanatory power indicates that (unpriced) risk factors that are orthogonal to the priced factors of either the CAPM or the ICAPM drive most of the time-series variation in HML_{Inter}. Finally, all these patterns continue to hold when we examine separately the pre-1990 and the post-1990 samples, as the next two panels of the table show.

Figure 4 illustrates visually the ability of the market and the ICAPM news terms to explain the time-series fluctuations of HML, HML_{Intra}, and HML_{Inter} (respectively, in Panels A, B, and C). Each panel shows the EWMA-smoothed log returns on one of the three portfolios, together with the fitted value from the multivariate regressions of Table 3 (the "ICAPM fit", red dashed), and the fitted value from the regression on the market alone (the "CAPM fit", green dotted).[15]

Starting from HML, Panel A shows the remarkable success of the ICAPM in explaining the variability of HML since the 1960s: the ICAPM fit closely tracks HML during its various booms and busts. In particular, the ICAPM explains a large fraction of HML's performance during the major crashes that occurred during this period. These value busts include several crashes in the 70s and 80s, the tech cycle in the 90s, the financial crisis, and the Covid-19 pandemic (though during the Covid-19 pandemic, as we study in greater detail below, there is a nontrivial part of unexplained variation in HML, reflecting the uniqueness of the Covid-19 episode). In contrast, the market factor explains almost none of the variation of HML during the last 60 years. That said, there are some features of the returns of HML that are not fully captured by the ICAPM. For example, the ICAPM cannot explain the protracted underperformance of HML in the last 15 years: while the actual return of HML has been persistently negative over that period, the fitted value fluctuates around zero, before turning clearly negative starting in 2015.

Panels B and C of the figure repeat the exercise for HML_{Intra} and HML_{Inter}, respectively. They show that the ICAPM has a similar (though slightly lower) explanatory power for the fluctuations in HML_{Intra}, whereas the shocks to HML_{Inter} are difficult to explain for either the CAPM or the ICAPM (and this inability is evident in crashes, including the financial crisis and the Covid-19 episode, as well).

Finally, in Figure 5, we decompose the returns of the ICAPM fit into the part that is attributed to discount rate, cash flow, and variance news. Panel A reports the decomposition

[15] As we are smoothing log returns, we generate the corresponding fitted values from regressions of log returns on news terms. The resulting betas are qualitatively similar, with extremely minor differences. We report those regressions in the Appendix.

for HML, whereas the other two panels show the decomposition for $\text{HML}_{\text{Intra}}$ and $\text{HML}_{\text{Inter}}$.

Whereas the variation in $\text{HML}_{\text{Inter}}$ over time is mostly attributed to discount rate news, the various cycles in HML and in $\text{HML}_{\text{Intra}}$ have different proximate causes. Some periods see offsetting effects of the different news terms (for example, in the 70s, when discount rate and variance news contributed positively to the HML and $\text{HML}_{\text{Intra}}$ returns, while cash flow news contributed negatively). Other times, all three news terms push HML's return in the same direction – for example, positively in the 2000s before the financial crisis, and negatively during the Covid-19 crash. Given the close relation between HML and $\text{HML}_{\text{Intra}}$, it is not surprising that the decomposition looks highly similar across the two.

To summarize, in this subsection we show that the ICAPM news terms help explain a large fraction of the variability of HML's return (and the intra-industry component) over time, and can be used to understand the drivers of the booms and busts of value investing.

3.3 Other factors and anomalies

In this subsection, we document how exposure to ICAPM news terms varies more broadly for other factors and anomalies in the empirical literature. Given our focus on value investing, we first decompose HML into intra- and inter-industry components within the large-cap and small-cap portions of the stock market. Rows (1) - (4) of Table 4 show that the improvement in R^2 is higher for the small-cap intra- and inter-industry components of HML, especially the inter-industry component, primarily because these components are more sensitive to aggregate discount-rate news. Within both the large-cap and small-cap component of HML, we continue to find that the intra-industry component is riskier in terms of cash-flow and variance betas. Since both these small-cap and large-cap value strategies derive most of their abnormal return from their intra-industry component, this more granular analysis is consistent with CGPT's ICAPM.

The table then reports the extent to which the other non-market Fama-French-Carhart factors load on the ICAPM. We find that the ICAPM produces relatively high R^2s for the size and investment factors. The ICAPM R^2 is 21.5% for SMB, Fama and French's size factor, which is higher than its CAPM R^2 of 15.5%. We find that the ICAPM R^2 for their investment factor, CMA, is 37.5%. That explanatory power is more than double that of the CAPM (R^2 of 15.2%). For both of these factors, the ICAPM loadings are of the correct sign to help explain the premia on those two factors.

However, the ICAPM R^2 is rather poor for the profitability factor, RMW. That factor's ICAPM R^2 is only 2.55% (which is lower than its CAPM R^2 of 3.28% because of the adjustment for the loss of two additional degrees of freedom). Though the ICAPM R^2 for the momentum factor, MOM, is 11.61%, which is higher than its CAPM R^2 of 5.39%, all three of momentum's ICAPM betas are of the wrong sign to explain the positive average return to momentum trading. Of course, the inability of the ICAPM to explain momentum may not be that surprising, as most researchers view a risk-based explanation of the momentum effect as unlikely.

In the last row of the table, we measure the CAPM and ICAPM betas of the fundamental-to-market (F-M) factor of Goncalves and Leonard (2023). Consistent with the ICAPM, F-M has a positive cash-flow beta that is economically and statistically significant when measured in a multiple regression. However, in contrast to HML and $\text{HML}_{\text{Intra}}$, F-M has a positive, though statistically insignificant, variance beta.[16] The ICAPM R^2 for F-M is higher than the CAPM R^2 of 7.4% but remains fairly modest at 13.4%.

Of course, there are hundreds of anomalous trading strategies documented in the empirical asset-pricing literature. To underscore the improvement in explanatory power that the ICAPM provides, we turn to the 193 anomalies replicated in Hou, Xue, and Zhang (2020). One benefit of those data, relative to otherwise similar datasets, such as the open-source data of Chen and Zimmermann (2022), is that Hou, Xue, and Zhang (2020) categorize their 193 anomalies into six subsets (strategies based on either value-versus-growth, intangibles, investment, profitability, momentum, or frictions). We rely on their categorizations to guide and constrain our analysis, as Table 4 documents that the ICAPM's improvement is far from uniform across the five Fama-French-Carhart non-market factors.

In the six panels of Figure 6, we report the cdfs of the resulting adjusted R^2s when explaining the quarterly returns on the anomalies within each of these six subsets. Consistent with our findings in Table 4, the improvement in explanatory power for the ICAPM relative to the CAPM is clearly evident for the value, intangibles, and investment classes of anomalies. These findings confirm that the ICAPM does substantially better than the CAPM in explaining the realized returns on an economically important portion of the cross-section of

[16] In unreported pricing tests, we find that F-M does not subsume $\text{HML}_{\text{Intra}}$, though $\text{HML}_{\text{Intra}}$ does not subsume F-M either.

average returns. However, for the remaining three classes of anomalies, the ICAPM does not offer that much improvement relative to the CAPM.

3.4 Robustness of the HML decomposition

For robustness, we also consider several alternative ways to decompose HML into intra-industry and inter-industry components, reporting detailed results for these alternatives in the online appendix.

In a first alternative decomposition, we retain the structure of our basic approach, but use 17 aggregated Fama-French industries rather than 48.

In a second alternative decomposition, we construct the intra-industry HML portfolio by following the same procedure Fama and French (1993) use to build HML, using stocks from all industries but cross-sectionally demeaning the book-to-market ratio within each industry. This procedure is the one used in Novy-Marx (2012). As also discussed in that paper, this intra-industry component has some residual industry exposure, which can be offset with corresponding positions in the underlying industries, obtaining an intra-industry HML component that is fully industry-neutral. As before, we construct $\text{HML}_{\text{Inter}}$ as the residual of a projection of HML onto the intra-industry component, and build $\text{HML}_{\text{Intra}}$ by rescaling the intra-industry component so the regression coefficient is 1.

In a third alternative decomposition, we compute an inter-industry HML portfolio, $\text{HML}_{\text{InterDirect}}$, defined as the portfolio of industries held in the same proportion as HML's industry exposures. Subtracting $\text{HML}_{\text{InterDirect}}$ from HML gives a portfolio that is, by construction, industry-neutral, which is our second alternative version of $\text{HML}_{\text{Intra}}$. We again construct $\text{HML}_{\text{Inter}}$ as the residual of a projection of HML onto the intra-industry component, and build $\text{HML}_{\text{Intra}}$ by rescaling the intra-industry component so the regression coefficient is 1.

The appendix shows that all three of these alternative HML decompositions deliver results that are broadly comparable to those we report in the paper for our basic decomposition.

4 A Daily ICAPM Decomposition of Inter- and Intra-industry HML Returns

So far, we have conducted all the analysis at the quarterly frequency, following Campbell and Vuolteenaho (2004), Campbell, Giglio and Polk (2013), and CGPT. As these papers discuss, a quarterly first-order VAR allows us to capture the long-term dynamics of the state variables very well and can be estimated based on nearly a century of data.

A shortcoming of the quarterly VAR specification is that it produces news terms at that same (quarterly) frequency. This aspect is sufficient for studying fluctuations in HML at relatively low frequencies, but is of limited help to understand episodes that unfold at higher frequencies. An interesting example is the Covid-19 market crash and subsequent recovery, which occurred rapidly over the span of a few quarters in 2020.

In this section we extend the VAR methodology to estimate the ICAPM news terms at the daily frequency. We do so by combining information from the quarterly VAR (specifically, the mapping between innovations in the state variables and aggregate news terms) and from a daily VAR that captures the evolution of the state variables at high frequency. We then use the estimated daily news terms to zoom into the Covid-19 episode.

4.1 Methodology

Our methodology combines the quarterly VAR estimated over the full sample (1926Q3 to 2022Q1), with a daily VAR estimated over a shorter sample (1990-01-04 to 2022-03-31), to obtain *daily* series for N_{DR}, N_{CF}, and N_V. The daily VAR is used to obtain within-quarter (daily) innovations in the state variables. The quarterly VAR is used to map these innovations in the state variables to long-run news about future returns, cash flows, and variance.

As discussed in section 2.1, under the assumptions maintained by CV, Campbell, Giglio and Polk (2013), and CGPT, namely, that the quarterly VAR (with state vector $\mathbf{x}_t$) captures the long-run dynamics of those variables well, the news terms in equations (2), (3), and (4) can be written as a linear function of the *innovations* in $\mathbf{x}_t$, $\eta_{t+1} \equiv \mathbf{x}_{t+1} - E_t\mathbf{x}_{t+1}$. The mapping from VAR innovations to the news terms is captured by the vectors $\lambda_{DR}, \lambda_{CF}$ and λ_V. For example, for the case of volatility, we have $N_{V,t+1} = \lambda_V \eta_{t+1}$, as described in section 2.1. The quarterly news shocks are therefore constructed by first computing quarterly innovations in $\mathbf{x}_t$ (i.e., the innovations from the quarterly VAR, η_{t+1}), and then mapping those innovations into long-term news (via the λs, estimated from the same VAR).

Using a quarterly VAR, one can therefore only compute news shocks at the quarterly frequency. The procedure we present in this section augments this setup with a higher-frequency VAR that allows us to track the innovations in $\mathbf{x}_t$ *within* the quarter. To do so, we focus on a (shorter) sample for which we observe, at the daily frequency, a set of state variables that can be used to construct *daily* innovations in $\mathbf{x}_t$, that can be then mapped into daily news terms via the vectors λ.

We proceed as follows. Denote days by the subscript s, and call $\tilde{\mathbf{x}}_s$ the vector of daily variables (which, in general, is different from the vector of variables that enter the quarterly VAR, $\mathbf{x}_s$). We begin by estimating a first-order daily VAR, which gives us daily innovations in $\tilde{\mathbf{x}}_s$ as well as its daily dynamics (e.g., the daily transition matrix $\tilde{\Gamma}$).

Next, we use the estimated daily VAR to compute daily innovations in the state variables that enter the quarterly VAR, $\mathbf{x}_s$. To do so, we proceed as follows. First, recall that the first element of $\mathbf{x}_s$ is the trailing 60-trading-day log real return of the market. The daily innovation in this variable is:

$$\mathbf{e}_1'(\mathbf{x}_s - E_{s-1}\mathbf{x}_s) = \sum_{j=0}^{59} r_{s-j} - E_{s-1}\left[\sum_{j=0}^{59} r_{s-j}\right] = r_s - E_{s-1}\left[r_s\right] = \mathbf{e}_1'(\tilde{\mathbf{x}}_s - E_{s-1}\tilde{\mathbf{x}}_s)$$

where the log real market return is also the first element of the daily state vector $\tilde{\mathbf{x}}_s$; this result follows from the fact that as of time $s-1$, the returns for the 59 days up to $s-1$ are known.

The second element in $\mathbf{x}_s$ is $EVAR_s$, that is, $E_s[\sum_{j=1}^{60} R_{s+j}^2]$. Using the estimated intercept and transition matrix from the daily VAR, we can compute $E_s[\sum_{j=1}^{60} R_{s+j}^2]$, and therefore its daily innovations, as long as R_s^2, the squared market return, is included in the daily state vector. The other elements of the quarterly VAR (PE ratio, term spread, default spread, and value spread) are observed at the daily frequency, so the daily innovations can be read directly from the daily VAR as long as these variables are included in $\tilde{\mathbf{x}}_s$.

Motivated by the discussion above, our daily state vector $\tilde{\mathbf{x}}_s$ includes the daily log market return r_s, the squared market return, R_s^2, the PE ratio, the term spread, the default spread, and the value spread. In addition, we also include in $\tilde{\mathbf{x}}_s$ variables that are useful to predict returns and variances at high frequencies, and that are available at the daily frequency in the sample we use for estimation (1990-01-04 to 2022-03-31): the 60-day rolling sum of the log market return, the 60-day rolling sum of the squared return, and the VIX (which is particularly useful to predict realized variance, see, for example, Berger et al. 2020).

Once we have obtained daily innovations in the quarterly state variables, ($\tilde{\eta}_s \equiv \mathbf{x}_s - E_{s-1}\mathbf{x}_s$), we combine them with the λ vectors that map the innovations in the quarterly state variables into the three news terms, obtaining daily news series. For example, for the case of volatility, we will have:

$$N_{V,s+1} = \lambda_V \tilde{\eta}_{s+1}$$

Before moving to the empirical results, it is useful to discuss how we can interpret the combination of VARs estimated at different frequencies and using different state variables. Ideally, we would want to use one specification for the entire analysis – the "true" time-series model incorporating the investors' full information set, with all the correct predictors (e.g., including VIX), at the highest possible frequency. In practice, however, some series are not available at the daily frequency for a very long period, and correctly capturing the long-term dynamics that play an essential role when computing these news terms would likely require a much richer specification than simply a first-order daily VAR.

Our procedure combining the two VARs at different frequencies can be interpreted as an approximation of the way an investor facing data limitations similar to the ones we face would compute the news shocks. To learn the mapping between the current state variables $\mathbf{x}_t$ and long-term expectations of returns, cash flows, and volatility (i.e., to compute the λs for the three news terms), one may want to sacrifice some potentially informative variables like the VIX that are only available for a short period, in exchange for having a long time series for the remaining variables. Therefore, an investor might want to use the quarterly VAR with a long time series to learn about the long-run responses of returns and volatility and estimate the λs.

Given that the additional variables we include in the daily VAR (especially the VIX) have been shown to have predictive power mostly for the short-run evolution of volatility (again, see Berger et al. 2020), we do not believe that their omission from the quarterly VAR would induce a substantial bias for estimating λ. However, to identify the daily shocks to $\mathbf{x}_t$, the investor may want to instead use the full daily VAR, with all predictors available at higher frequency, even if for a shorter sample, since the forecasts from the daily VAR only need to cover a 60 trading day horizon as an input for the news terms.[17]

4.2 Results

In the Appendix we report the results of the daily VAR estimation. Many of the patterns are similar to the ones we find in the quarterly VAR: for example, the PE ratio and the default spread help predict returns. Consistent with previous research, we find that the VIX plays an important role in predicting future realized variance (squared returns) even after controlling for lagged realized variance.

After building the daily news terms as described in the previous section, we next compare the estimated daily news with the news from the quarterly VAR. Note that, in theory, the daily news do not exactly sum up to the quarterly news within each quarter. The reason is that the innovations in $\mathbf{x}_s$ from the daily VAR (from which the news terms are constructed) do *not* add up to the quarterly innovations $\mathbf{x}_t$, since in the quarterly VAR we use time-t information to predict $\mathbf{x}_t$ over the entire following quarter, whereas in the daily analysis we try to predict $\mathbf{x}_s$ day by day.[18]

That said, we do find that empirically the two are quite close: the sums of the daily news terms N_{DR}, N_{CF}, and N_V within each quarter are highly correlated with the quarterly news series obtained directly from the quarterly VAR. The correlations of the news terms are 0.95, 0.97 and 0.71 respectively for N_{DR}, N_{CF}, and N_V. Figure 7 shows the three news terms (one per panel) estimated using the quarterly VAR (solid line) and the daily VAR (dashed line). The figure smooths the series using the same EWMA as in Figure 3.[19]

We next reexamine the ICAPM explanation for the fluctuations in HML using the daily

[17] An alternative approach would be to estimate a mixed-frequency model to jointly estimate both the daily news and the long-run dynamics of the variables in $\mathbf{x}_t$. Work by Ghysels, Santa-Clara, and Valkanov (2005, 2006) and Ghysels, Sinko, and Valkanov (2007) has documented the usefulness of such a technique. However, this would be computationally more complex, and we leave it for future research. In contrast, our approach is simple to implement and easily interpretable.

[18] More formally, the innovations from the quarterly VAR can be written, using the daily notation, as $\eta_{s+60} = \mathbf{x}_{s+60} - E_s\mathbf{x}_{s+60}$. Since the daily innovations are $\tilde{\eta}_{s+1} = \mathbf{x}_{s+1} - E_s\mathbf{x}_{s+1}$, then

$$\sum_{j=1}^{60} \tilde{\eta}_{s+j} = \sum_{j=1}^{60} (\mathbf{x}_{s+j} - E_{s+j-1}\mathbf{x}_{s+j}) \neq \mathbf{x}_{s+60} - E_s\mathbf{x}_{s+60} = \eta_{s+60}$$

[19] We initialize the EWMA filter to zero.

news. We begin by reporting in Table 5 the exposure of HML to the three news terms over the 1990Q2-2022Q1 sample. Each row in the panel corresponds to a different regression of the three portfolios (HML, $\text{HML}_{\text{Intra}}$, and $\text{HML}_{\text{Inter}}$), onto the three news terms, using a different construction of the news series and data frequency. Specifically, the first row of each panel reports the regression using the quarterly news series (at the quarterly frequency): that is, the same as in Panel C of Table 3, i.e., for the post-1990 sample. As before, we find that HML has a negative discount rate beta, positive cash flow beta, and negative variance beta; and again, the regression has a high time-series R^2 for HML and $\text{HML}_{\text{Intra}}$, and much lower R^2 for $\text{HML}_{\text{Inter}}$.

The second row of each panel uses the daily news series aggregated to a quarterly frequency (by summing the daily news within the quarter), and then estimates the betas of the three portfolios with respect to the news terms using quarterly data. The results are very similar to the ones in the first row, showing that at the quarterly frequency, there is little difference between using the daily or quarterly VAR to estimate the news terms.

The last rows of each panel report daily betas, obtained using the daily news terms (and the daily returns on the three portfolios). For comparability with the quarterly analysis, we include 59 lags of each news term (i.e., roughly a quarter of daily news), though results are qualitatively similar if we only estimate betas using the contemporaneous daily shock. Table 5 reports the sum of the betas on each news term from that regression.[20] The R^2 is lower (as we are now trying to explain daily fluctuations in HML, $\text{HML}_{\text{Intra}}$ and $\text{HML}_{\text{Inter}}$), but is still quite high (28%, 24%, and 15% respectively). The signs of the betas are always the same as in the quarterly case.

Overall, Table 5 and Figure 7 show that at lower frequencies (quarterly), estimating the news daily makes little difference to the results. The main advantage of the daily news estimation is the ability to zoom into specific episodes, studying them at high frequency.

Figure 8 uses the beta estimates from this table to show the time series of the fitted HML (Panel A), $\text{HML}_{\text{Intra}}$ (Panel B) and $\text{HML}_{\text{Inter}}$ (Panel C) against the original series. Each figure reports the ICAPM fit obtained using quarterly data (dashed red), using the daily news series aggregated to the quarterly frequency (solid red), and using the daily regression (green). There are two interesting patterns in this figure. First, fitting the portfolios using quarterly as opposed to daily regressions yields a better overall fit – more so for $\text{HML}_{\text{Intra}}$

[20]The appendix plots how the estimated coefficients evolve as a function of lag.

and $\text{HML}_{\text{Inter}}$ than for HML. This worse fit may arise from either additional measurement error in the daily series or from asset returns that do not immediately reflect information in the daily news.

Second, and despite the worse fit, for all three series, the daily ICAPM does a better job in capturing the most severe booms and busts of HML, including, and most interestingly, the Covid-19 pandemic. The ICAPM fit for $\text{HML}_{\text{Inter}}$ is poor regardless of the estimation frequency.

We conclude this section by zooming into the Covid-19 episode of 2020. Figures 9, 10, and 11 show the news terms, the ICAPM fit, and the components of that ICAPM fit, respectively, during 2020. In Figure 9, we plot both the quarterly and daily news terms, and we do *not* smooth them using an EWMA as in the previous figures so that the daily variation appears clearly (we instead report cumulative news terms, demeaned within this year to focus on the high-frequency variation). Clearly, the quarterly news can only give us a very coarse picture of the events of 2020, since it includes just four data points for the year. The daily news give us a much higher frequency account of the events, including the very rapid developments in February 2020, and the arrival of large news terms at other points in the year. Perhaps most interesting are the dynamics of volatility, in Panel C: the daily news series captures an extreme, but transitory, peak that is in large part missed by the quarterly series, and is reverted substantially before the end of the second quarter.

Figure 10 shows how HML and its components fared during this period. The figure shows that the daily ICAPM fit tracks the high-frequency movements of HML during the year, in a way that is almost entirely missed by the quarterly news. During the Covid-19 pandemic, even $\text{HML}_{\text{Inter}}$'s fluctuations are explained by the ICAPM to some degree – though the explanatory power for HML and $\text{HML}_{\text{Intra}}$, is, as usual, much higher.

As discussed above, the Covid-19 pandemic was characterized by the arrival of large cash-flow, discount rate, and volatility shocks. Exposure to these three shocks goes a long way to explain not only why HML dropped substantially at the beginning of 2020, but also why it recovered towards the end of the year.

We again decompose the ICAPM fit into the part that is attributed to discount rate, cash flow, and variance news focusing on 2020. Figure 11, Panel A, reports the decomposition for HML, whereas the other two panels show the decomposition for $\text{HML}_{\text{Intra}}$ and $\text{HML}_{\text{Inter}}$.

The figure shows that though HML was buffeted by all three shocks in 2020, the volatility and discount-rate news shocks largely offset each other. In contrast, cash-flow news is the primary driver of the component of value returns attributable to the ICAPM. Consistent with our previous results, this decomposition of HML's ICAPM fit is mainly attributable to the intra-industry component of HML. In constrast, variation in the ICAPM fit of the inter-industry component of HML comes primarily from discount-rate news.

To conclude, in this section we showed that the ICAPM news terms help explain a large fraction of the variability of HML's return (and the intra-industry component) over time, and can be used to understand the drivers of the booms and busts of value investing.

We summarize our findings with a variance decomposition of value returns. Specifically, Table 6 reports the percentage of return variation explained by each of the three ICAPM shocks, at both the quarterly and daily frequency, for HML, $\mathrm{HML}_{\mathrm{Intra}}$, and $\mathrm{HML}_{\mathrm{Inter}}$. Panel A shows that the ICAPM explains roughly half of the variation in quarterly HML returns over the 1963Q3-2022Q1 sample. The majority of that explanatory power comes from the intra-industry component of HML. That component is primarily explained by cash-flow (13%) and variance news (18%). In contrast, most of the variation in inter-industry HML is unexplained (86%), and any explanatory power comes entirely from aggregate discount-rate news. When we move to the daily frequency, we continue to find that the ICAPM explains relatively more of the intra-industry component of HML (26% compared to only 16% for inter-industry HML). Interestingly, during 2020 and 2021, there was a significant increase in the contribution of cash-flow news to the variation in both components of HML, and especially the intra-industry component (23%).

5 Earnings Shocks and Industry Shocks During the Covid-19 Pandemic

In the previous sections, we showed that the ICAPM model is able to explain a non-trivial portion of the movements of HML during the pandemic. However, the explanatory power of the ICAPM comes relatively more from the intra-industry component of HML. The inter-industry component of HML (that is, the return of the portfolio of industries that HML is exposed to) also suffered during the pandemic, in a way that the ICAPM does not explain.

In this section, we look directly at the earnings of the industries that HML is exposed to during 2020, a period that saw large industry-specific shocks related to the Covid-19 pandemic. We show that HML underperformed during the pandemic beyond its exposure to aggregate news, because it happened to be long industries whose earnings were poor during the pandemic, and short industries whose earnings did relatively better during the pandemic. These earnings patterns do not simply reflect exposure to aggregate cash flow news, which we believe is the reason why the ICAPM does not explain well the returns of the inter-industry component of HML during this period.

To study the earnings of the industries that HML is exposed to, we proceed as follows. We first compute the weight of HML in each industry (that is, the weights used to build $\text{HML}_{\text{InterDirect}}$). Then, we separately consider a portfolio that buys all industries in which HML has long exposure (L), and the portfolio that buys all industries in which HML has short exposure (S). We refer to the former as "value industries" and to the latter as "growth industries".

For each of the two portfolios, $p = \{L, S\}$, call w_{it}^p the weight of stock i in HML as of the end of quarter t. For each stock i, MV_{it} is the market value at the end of quarter t, E_{it} the total earnings during quarter t, and BE_{it} the total book equity as of end of quarter t. For each portfolio $p = \{L, S\}$, we construct an aggregated measure of earnings during quarter t scaled by the previous quarter's book equity:

$$ScaledEarn_t^p = \frac{\sum_i w_{it-1}^p E_{i,t}/MV_{it-1}}{\sum_i w_{it-1}^p BE_{it-1}/MV_{it-1}} \tag{7}$$

Note that for a value-weight portfolio, weights are proportional to market cap, so that this formula reduces to the total earnings over the previous-quarter total book equity of the portfolio. We construct these scaled earnings for the four quarters of 2020, and then, starting from $t = 2020q1$, we build a cumulated series ("cumulated scaled earnings") during the year, which we study in the figures described below.

The top panel of Figure 12 shows the cumulated scaled earnings for the portfolio of value industries and growth industries, with black and red lines respectively. The figure shows that during 2020, value industries had relatively flat earnings, whereas growth industries tended to have relatively good earnings.

Next, we study how these industry earnings relate to the aggregate earnings during this period (the component that most closely corresponds to the ICAPM's cash-flow news). We compute the cumulated scaled earnings at horizons from 1 to 4 quarters for the two portfolios going back to 1973, and we compute an analogous measure for the aggregate market. We then regress the former on the latter, and plot in the bottom panel of Figure 12 the residuals. The figure therefore shows the behavior of that part of earnings of the various industries that is not explained by the industries' exposure to aggregate earnings shocks.

The figure shows that the adjustment for the exposure to aggregate earnings shocks lowers the cumulative earnings for both the value and growth industry portfolios. The adjustment does capture some of the variation of the earnings across industries in this period, but the difference between the earnings of value and growth industries in HML follows a pattern similar to the top panel: value industries had poor (negative, on average) earnings, and growth industries had better earnings (positive, on average) during 2020.

Finally, we decompose these results by industry, in the two panels of figure 13. For each of the 48 industries, we compute the contribution of that industry to the cumulative scaled earnings of the value and growth portfolios during 2020 (described in equation 7). The top panel plots this contribution against the weight of that industry in HML. So the industries on the left side of the figure are "growth industries" (portfolio S), and industries on the right side are "value industries" (portfolio L). The figure shows that HML has no exposure to the vast majority of industries. Some industries, however, are significantly weighted by HML over this period, positively (e.g., oil and banks), or negatively (business services, drugs).

The earnings of the value industries in 2020 were mixed, as some (banks) had good earnings and others (oil) had negative earnings during the pandemic. The performance of the growth industries (that enter negatively into HML) was instead uniformly good, for reasons that are clearly idiosyncratic to the pandemic. This fact explains the patterns we observe at the aggregate level in Figure 12. The bottom panel of Figure 13 repeats the exercise but with the residuals (thus aggregating up to the bottom panel of Figure 12), finding similar results.

Overall, these results show that the Covid-19 pandemic featured important industry-specific shocks to earnings, that went beyond what can be explained by the different industries' exposure to cash flow news. Our findings help explain why the ICAPM can account for only a small fraction of the fluctuations in $\text{HML}_{\text{Inter}}$ over this episode.

6 Conclusion

We show that the ICAPM, in stark contrast to the static CAPM, explains a significant portion of the realized returns on value-minus-growth strategies (like Fama and French's (1993) HML) and thus can justify the large swings in the fortunes of value investors over the last 60 years. A key implication of the ICAPM is that investors price exposure to three main sources of risk, captured by cash-flow news, discount-rate news, and volatility news. Previous literature has shown that HML is significantly exposed to all news terms, in a way that can explain its high expected return. In this paper, we show that the exposure to the three shocks actually accounts for a large part of the time-series variation in HML's returns: the differential exposures of value and growth stocks to these three key drivers of returns, measured using a quarterly vector autoregression, explain roughly half of its realized quarterly returns.

The classic value strategy bets on the convergence of valuation ratios both across and within industries. However, the intra-industry component of such a bet typically contributes much more to value's average outperformance. We exploit this distinction to discipline our ICAPM interpretation of the drivers of the returns to value investing. If the ICAPM is a useful model of expected returns, the intra-industry component of value should load more on ICAPM shocks, especially those that command a higher price of risk.

Our results fare well in the face of this refinement. We find that the ICAPM does a much better job of explaining the realized returns on the intra-industry component of a value-minus-growth bet. Moreover, intra-industry value is especially sensitive to cash-flow and volatility news, the two ICAPM factors that command a much higher risk premium. In contrast, the ICAPM does not explain inter-industry value as well, and any explanatory power comes primarily from discount-rate news, the ICAPM factor that commands a much lower risk premium.

We also study the explanatory power of ICAPM shocks for the returns to other investment strategies that have been explored in the enormous literature on equity market factors and anomalies. We find that the ICAPM has good explanatory power for the Fama-French size and investment factors but not for the profitability factor or the Carhart momentum factor. We obtain comparable results when we look at 193 equity anomalies replicated and categorized by Hou, Xue, and Zhang (2020): anomalies related to value, intangibles, and investment are better explained by the ICAPM than anomalies related to profitability, momentum, or frictions.

Previous research typically measures ICAPM news terms at the monthly or quarterly frequency, so that the crucial low-frequency dynamics of aggregate risks and returns can be measured precisely, over as long a sample as possible. However, aggregate discount-rate, cash-flow, and variance news can instantaneously move market prices in a substantial fashion. As a consequence, the potential benefits of an ICAPM perspective to explain *realized* returns, especially the sorts of sharp booms and busts that one observes in value returns, may be limited by this aspect of existing methods.

We fill this gap by developing a novel methodology that marries low-frequency and high-frequency VARs to generate daily ICAPM news terms. Our technique retains the valuable information about the low-frequency component of aggregate risks and returns that a long sample based on infrequent data (e.g., accounting-based valuation ratios) can bring while also adding the incremental information in novel high-frequency data, often only available in recent subsamples (e.g., VIX), concerning the high-frequency dynamics of those key low-frequency state variables driving aggregate risks and returns.

With our new method in hand, we then confirm that the aforementioned conclusions about the relative importance of the CAPM and the ICAPM across the intra- and inter-industry components of *quarterly* value returns are also evident in the *daily* movements of value-minus-growth returns, especially during the Covid-19 pandemic. Cash-flow news drove a significant proportion of the returns on intra-industry value in 2020, while inter-industry value was not well-explained by the ICAPM. Instead, shocks to the relative earnings of value and growth industries were key drivers of the returns to inter-industry value during the pandemic.

The large literature on the value premium and other asset pricing anomalies has mostly focused on explaining cross-sectional patterns in average returns. The main reason for this is that theory has clear predictions about the relation between risk exposures and risk premia, but existing models are often silent on the sources of time-series variation in returns (especially the component that is driven by unpriced risks). Studying the time-series fluctuations of returns for diversified portfolios like HML, including attributing them to priced and unpriced risks – as we do in our paper – is a step towards a deeper understanding of anomaly returns, and can guide the development of theoretical models that aim to explain their fundamental sources.

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Table 1: **Cash-flow, Discount-rate, and Variance News for the Market Portfolio**

The table shows the correlations (off-diagonals) and standard deviations (diagonals) of cash-flow news (N_{CF}), negative discount-rate news ($-N_{DR}$), and volatility news (N_V) implied by the VAR model of Appendix Table 1.

News corr/std	N_{CF}	$-N_{DR}$	N_V
N_{CF}	0.035	0.408	-0.428
$-N_{DR}$	0.408	0.084	0.096
N_V	-0.428	0.096	0.026

Table 2: **HML: Intra- and Inter-industry Decomposition and CAPM pricing**

The table reports a decomposition of Fama and French's (1993) HML into its intra- and inter-industry components. We first create an HML portfolio within each industry in the same way as HML. We then combine these industry-specific HML portfolios using industry market weights. We define industries using Fama and French's (1997) mapping of SICC into 48 industries, based on historical classifications from Ken French's website. We scale the resulting composite portfolio so that a full-sample regression of HML on that scaled portfolio, the first regression in the table, has a unit loading. We define the scaled portfolio as $\text{HML}_{\text{Intra}}$ and the constant and residual from the regression as $\text{HML}_{\text{Inter}}$. The sample is 1963Q3-2022Q1. We report t-statistics in parentheses.

Panel A: Full-sample estimates

		constant	$\text{HML}_{\text{Intra}}$	HML	$RMRF$	$\widehat{R^2}$
(1)	HML	-0.39%	1.00			71.7%
		(-1.81)	(24.38)			
(2)	$\text{HML}_{\text{Intra}}$	0.65%		0.72		71.7%
		(3.63)		(24.38)		
(3)	$\text{HML}_{\text{Inter}}$	-0.65%		0.28		27.8%
		(-3.63)		(9.56)		
(4)	HML	1.24%			-0.17	5.5%
		(3.16)			(-3.83)	
(5)	$\text{HML}_{\text{Intra}}$	1.45%			-0.07	1.0%
		(4.25)			(-1.82)	
(6)	$\text{HML}_{\text{Inter}}$	-0.21%			-0.10	6.9%
		(-1.01)			(-4.27)	

Panel B: Pre-1990 estimates

		constant	HML_{Intra}	HML	$RMRF$	$\widehat{R^2}$
(1)	HML	-0.22%	0.88			63.0%
		(-0.66)	(13.47)			
(2)	HML_{Intra}	0.86%		0.72		63.0%
		(2.97)		(13.47)		
(3)	HML_{Inter}	-0.86%		0.28		19.5%
		(-2.97)		(5.17)		
(4)	HML	1.75%			-0.25	16.4%
		(3.76)			(-4.66)	
(5)	HML_{Intra}	2.09%			-0.15	6.6%
		(4.67)			(-2.91)	
(6)	HML_{Inter}	-0.34%			-0.10	6.4%
		(-1.11)			(-2.87)	

Panel C: Post-1990 estimates

		constant	HML_{Intra}	HML	$RMRF$	$\widehat{R^2}$
(1)	HML	-0.41%	1.08			76.8%
		(-1.42)	(20.53)			
(2)	HML_{Intra}	0.48%		0.71		76.8%
		(2.08)		(20.53)		
(3)	HML_{Inter}	-0.48%		0.29		34.8%
		(-2.08)		(8.29)		
(4)	HML	0.72%			-0.10	0.8%
		(1.18)			(-1.42)	
(5)	HML_{Intra}	0.82%			0.01	-0.8%
		(1.64)			(0.09)	
(6)	HML_{Inter}	-0.10%			-0.11	6.7%
		(-0.34)			(-3.18)	

Table 3: **Cash-flow, Discount-rate, and Variance Betas**

The table shows the estimated market ($\widehat{\beta}$), cash-flow ($\widehat{\beta}_{CF}$), discount-rate ($\widehat{\beta}_{DR}$), and variance ($\widehat{\beta}_V$) betas for HML and its intra- and inter-industry components. The left side of the table runs simple regressions while the right side of the table estimates a multiple regression with all three ICAPM News terms as regressors. The resulting point estimates in both the simple and multiple ICAPM regressions are scaled as in Campbell, Giglio, Polk, and Turley (2018). The sample is 1963Q3-2022Q1, which is then split into two sub-samples in Panels B (1963Q3-1990Q1) and C (1990Q2-2022Q1). We report t-statistics in parentheses.

		simple regressions				multiple regression			
		$\widehat{\beta}$	$\widehat{\beta}_{DR}$	$\widehat{\beta}_{CF}$	$\widehat{\beta}_V$	$\widehat{\beta}_{DR}$	$\widehat{\beta}_{CF}$	$\widehat{\beta}_V$	$\widehat{R^2}$
Panel A: Full Sample									
(1)	HML	-0.16	-0.24	0.09	-0.11	-0.27	0.10	-0.06	48.4%
		(-3.51)	(-6.77)	(6.14)	(-10.07)	(-8.13)	(7.61)	(-4.77)	
(2)	$\text{HML}_{\text{Intra}}$	-0.07	-0.15	0.07	-0.10	-0.15	0.07	-0.06	39.0%
		(-1.92)	(-4.59)	(6.13)	(-9.87)	(-4.83)	(5.81)	(-5.47)	
(3)	$\text{HML}_{\text{Inter}}$	-0.08	-0.10	0.01	-0.02	-0.12	0.03	0.00	12.7%
		(-3.50)	(-4.87)	(1.66)	(-2.65)	(-5.33)	(3.27)	(0.40)	
Panel B: Pre-1990									
(4)	HML	-0.25	-0.29	0.04	-0.10	-0.28	0.07	-0.04	50.2%
		(-4.75)	(-7.04)	(2.15)	(-8.00)	(-4.91)	(4.54)	(-2.13)	
(5)	$\text{HML}_{\text{Intra}}$	-0.17	-0.21	0.04	-0.07	-0.20	0.06	-0.03	34.0%
		(-3.33)	(-5.02)	(2.29)	(-6.00)	(-3.38)	(3.71)	(-1.57)	
(6)	$\text{HML}_{\text{Inter}}$	-0.08	-0.09	0.00	-0.02	-0.08	0.01	-0.01	6.1%
		(-2.40)	(-2.88)	(0.12)	(-2.70)	(-1.62)	(0.78)	(-0.58)	
Panel C: Post-1990									
(7)	HML	-0.06	-0.20	0.14	-0.13	-0.29	0.13	-0.06	48.5%
		(-0.92)	(-3.46)	(6.56)	(-6.71)	(-6.18)	(6.30)	(-3.09)	
(8)	$\text{HML}_{\text{Intra}}$	0.02	-0.09	0.11	-0.12	-0.14	0.09	-0.07	42.9%
		(0.41)	(-1.82)	(6.72)	(-7.64)	(-3.58)	(4.92)	(-4.23)	
(9)	$\text{HML}_{\text{Inter}}$	-0.09	-0.11	0.02	-0.01	-0.14	0.04	0.01	18.2%
		(-2.64)	(-4.05)	(2.06)	(-1.31)	(-5.10)	(3.44)	(0.85)	

Table 4: **Other Empirical Factors: ICAPM Betas**

The table shows the estimated market ($\widehat{\beta}$), cash-flow ($\widehat{\beta}_{CF}$), discount-rate ($\widehat{\beta}_{DR}$), and variance ($\widehat{\beta}_V$) betas for the intra- and inter-industry components of the large-cap and small-cap components of HML, for the other Fama-French-Carhart factors (SMB, RMW, CMA, and MOM), and for the FM factor of Goncalves and Leonard (2023). The left side of the table runs simple regressions while the right side of the table estimates a multiple regression with all three ICAPM News terms as regressors. The resulting point estimates in both the simple and multiple ICAPM regressions are scaled as in Campbell, Giglio, Polk, and Turley (2018). The sample is 1963Q3-2022Q1. We report t-statistics in parentheses.

		simple regressions					multiple regression			
		$\widehat{\beta}$	$\widehat{R^2}$	$\widehat{\beta}_{DR}$	$\widehat{\beta}_{CF}$	$\widehat{\beta}_V$	$\widehat{\beta}_{DR}$	$\widehat{\beta}_{CF}$	$\widehat{\beta}_V$	$\widehat{R^2}$
(1)	$\text{HML}^{\text{Large}}_{\text{Intra}}$	0.00	-0.4%	-0.08	0.07	-0.09	-0.07	0.06	-0.06	30.3%
		(0.10)		(-2.18)	(6.51)	(-8.56)	(-2.07)	(4.94)	(-5.23)	
(2)	$\text{HML}^{\text{Large}}_{\text{Inter}}$	-0.04	0.4%	-0.07	0.02	-0.02	-0.10	0.03	0.00	7.1%
		(-1.41)		(-2.65)	(2.56)	(-2.70)	(-3.14)	(3.06)	(-0.32)	
(3)	$\text{HML}^{\text{Small}}_{\text{Intra}}$	-0.14	4.1%	-0.20	0.05	-0.09	-0.21	0.06	-0.05	31.5%
		(-3.32)		(-5.72)	(4.23)	(-7.96)	(-5.69)	(4.63)	(-3.84)	
(4)	$\text{HML}^{\text{Small}}_{\text{Inter}}$	-0.15	8.6%	-0.17	0.02	-0.03	-0.20	0.04	0.00	20.0%
		(-4.81)		(-6.51)	(1.59)	(-3.76)	(-6.68)	(3.49)	(-0.18)	
(5)	SMB	0.26	15.5%	0.18	0.09	-0.02	0.11	0.07	0.00	21.5%
		(6.62)		(4.79)	(7.53)	(-1.30)	(2.73)	(5.46)	(-0.29)	
(6)	RMW	-0.09	3.3%	-0.08	-0.01	0.00	-0.08	0.00	0.00	2.6%
		(-2.99)		(-2.94)	(-1.48)	(-0.32)	(-2.48)	(-0.35)	(0.38)	
(7)	CMA	-0.19	15.2%	-0.22	0.02	-0.05	-0.25	0.04	-0.01	37.5%
		(-6.55)		(-9.28)	(2.27)	(-6.29)	(-9.42)	(4.76)	(-1.65)	
(8)	MOM	-0.21	5.4%	-0.13	-0.08	0.05	-0.15	-0.04	0.06	11.6%
		(-3.79)		(-2.65)	(-4.71)	(3.34)	(-2.58)	(-2.24)	(2.98)	
(9)	F-M	-0.25	7.4%	-0.26	0.01	-0.02	-0.34	0.06	0.03	13.4%
		(-3.94)		(-4.87)	(0.74)	(-1.22)	(-5.42)	(2.57)	(1.59)	

Table 5: **Explaining HML with Quarterly and Daily ICAPM News**

The table shows the estimated market ($\widehat{\beta}$), cash-flow ($\widehat{\beta}_{CF}$), discount-rate ($\widehat{\beta}_{DR}$), and variance ($\widehat{\beta}_{V}$) betas for HML (Panel A), $\text{HML}_{\text{Intra}}$ (Panel B), and $\text{HML}_{\text{Inter}}$ (Panel C) from a multiple regression with all three ICAPM News terms as regressors. In each Panel, the first regression uses quarterly news terms from the quarterly VAR; the second regression uses quarterly news terms constructed by summing daily news terms from the daily VAR; and the third regression uses daily news terms from the daily VAR. We scale the resulting point estimates as in Campbell, Giglio, Polk, and Turley (2018). The daily regressions estimating ICAPM betas include 59 lags (i.e., roughly a quarter of daily news); we report the sum of the resulting 60 coefficients associated with each news term. The sample is 1990Q2-2022Q1. We report t-statistics in parentheses.

	Frequency		Multiple Regression			
	Regression	VAR	$\widehat{\beta}_{DR}$	$\widehat{\beta}_{CF}$	$\widehat{\beta}_{V}$	$\widehat{R^2}$
		Panel A: HML				
(1)	Quarterly	Quarterly	-0.29	0.13	-0.06	48.5%
			(-6.18)	(6.30)	(-3.09)	
(2)	Quarterly	Daily	-0.21	0.10	-0.02	41.5%
			(-4.71)	(6.23)	(-1.58)	
(3)	Daily	Daily	-0.08	0.09	-0.02	27.8%
			(-1.63)	(6.68)	(-0.74)	
		Panel B: $\text{HML}_{\text{Intra}}$				
(4)	Quarterly	Quarterly	-0.14	0.09	-0.07	43.0%
			(-3.58)	(4.92)	(-4.23)	
(5)	Quarterly	Daily	-0.08	0.07	-0.03	38.1%
			(-2.19)	(5.00)	(-2.89)	
(6)	Daily	Daily	-0.01	0.06	-0.02	24.3%
			(-0.26)	(6.81)	(-1.93)	
		Panel C: $\text{HML}_{\text{Inter}}$				
(7)	Quarterly	Quarterly	-0.14	0.04	0.01	18.2%
			(-5.10)	(3.44)	(0.85)	
(8)	Quarterly	Daily	-0.13	0.03	0.01	17.4%
			(-5.01)	(3.57)	(1.45)	
(9)	Daily	Daily	-0.07	0.03	0.01	14.6%
			(-2.04)	(3.18)	(0.70)	

Table 6: **HML Variance Decomposition**

The table shows the variance decomposition of HML (Panel A) and its intra- (Panel B) and inter-industry (Panel C) components based on a multiple regression where all three ICAPM news terms are regressors. In each panel, the first two decompositions explain quarterly returns using ICAPM news implied by the quarterly VAR, and the final two decompositions explain daily returns using ICAPM news implied by the daily VAR. All four rows in each Panel use the full sample (quarterly: 1926Q3-2022Q1, daily: 1990-04-02 to 2022-03-31) when estimating news terms. When estimating betas, in each panel, the first row uses the 1963Q3-2022Q1 sample, the second row uses the 1990Q2-2022Q1 sample, and the third and fourth rows use the 1990-04-02 to 2022-03-31 sample. The daily regressions estimating ICAPM betas include 59 lags (i.e., roughly a quarter of daily news).

Var. Decomp Sample Period	Frequency	Std(HML)	Var. Decomp. (%) N_{DR}	 N_{CF}	 N_V	 Resid
Panel A: HML						
1963Q3-2022Q1	Quarterly	6.07%	18%	16%	15%	51%
1990Q2-2022Q1	Quarterly	6.68%	12%	25%	12%	50%
19900402-20220331	Daily	0.69%	4%	18%	7%	71%
20200102-20201231	Daily	1.62%	0%	28%	10%	63%
Panel B: HML_{Intra}						
1963Q3-2022Q1	Quarterly	5.14%	8%	13%	18%	60%
1990Q2-2022Q1	Quarterly	5.43%	4%	21%	19%	56%
19900402-20220331	Daily	0.41%	7%	14%	5%	74%
20200102-20201231	Daily	0.96%	1%	23%	9%	66%
Panel C: HML_{Inter}						
1963Q3-2022Q1	Quarterly	3.22%	12%	3%	-1%	86%
1990Q2-2022Q1	Quarterly	3.24%	15%	6%	-1%	80%
19900402-20220331	Daily	0.46%	2%	9%	5%	84%
20200102-20201231	Daily	0.84%	0%	21%	10%	69%

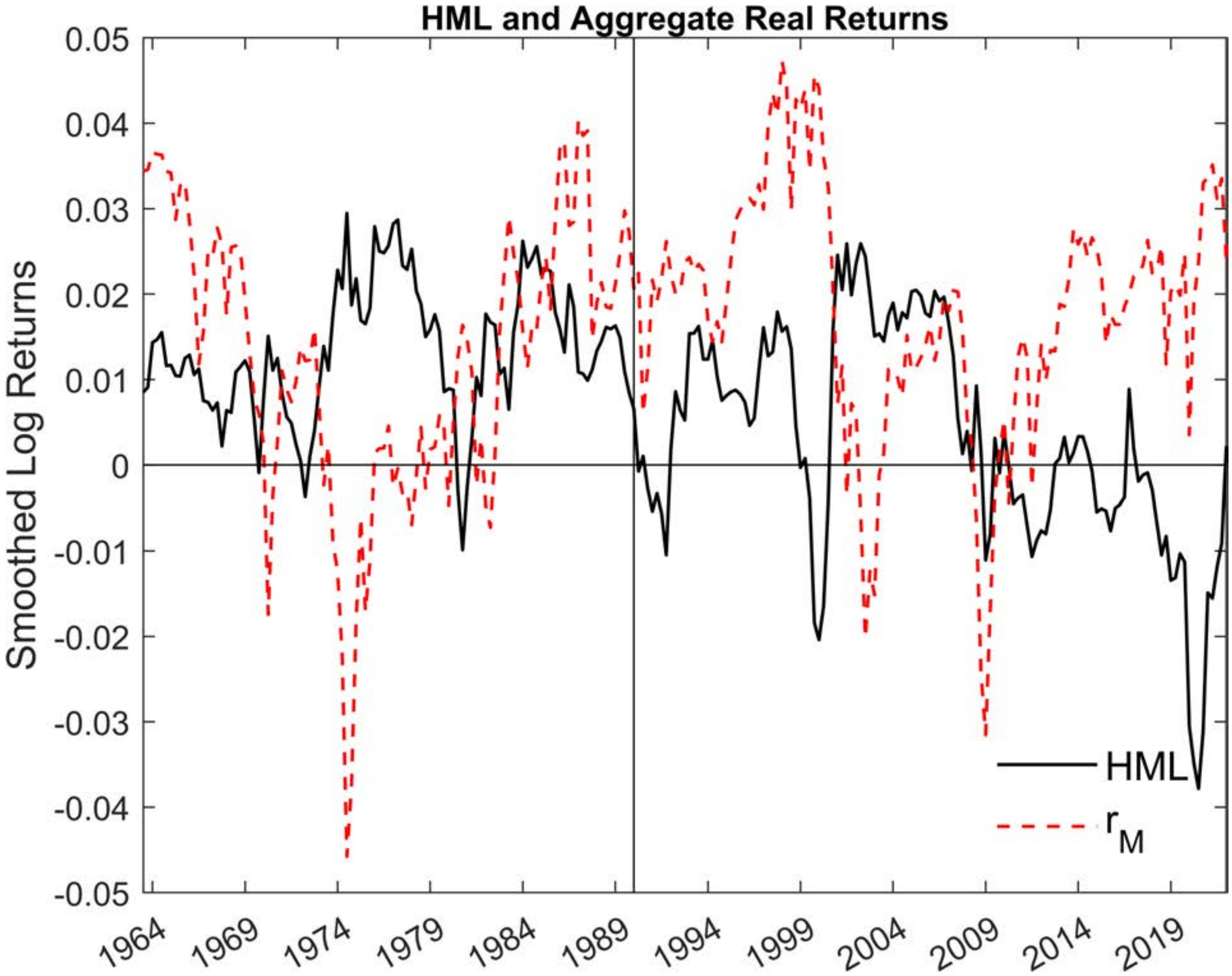

Figure 1: The figure plots the log return on HML (solid black line) and $\mathrm{r_M}$, the log real return on the market (dashed red line). The series are smoothed with a trailing exponentially weighted moving average in which the decay parameter is set to 0.08 per quarter, and the smoothed series is generated, for example, as $MA_t(\mathrm{HML}) = 0.08\mathrm{HML_t} + (1\text{-}0.08)MA_{t-1}(\mathrm{HML})$. This decay parameter implies a half-life of two years. The vertical line indicates the start of the subperiod 1990Q2-2022Q1.

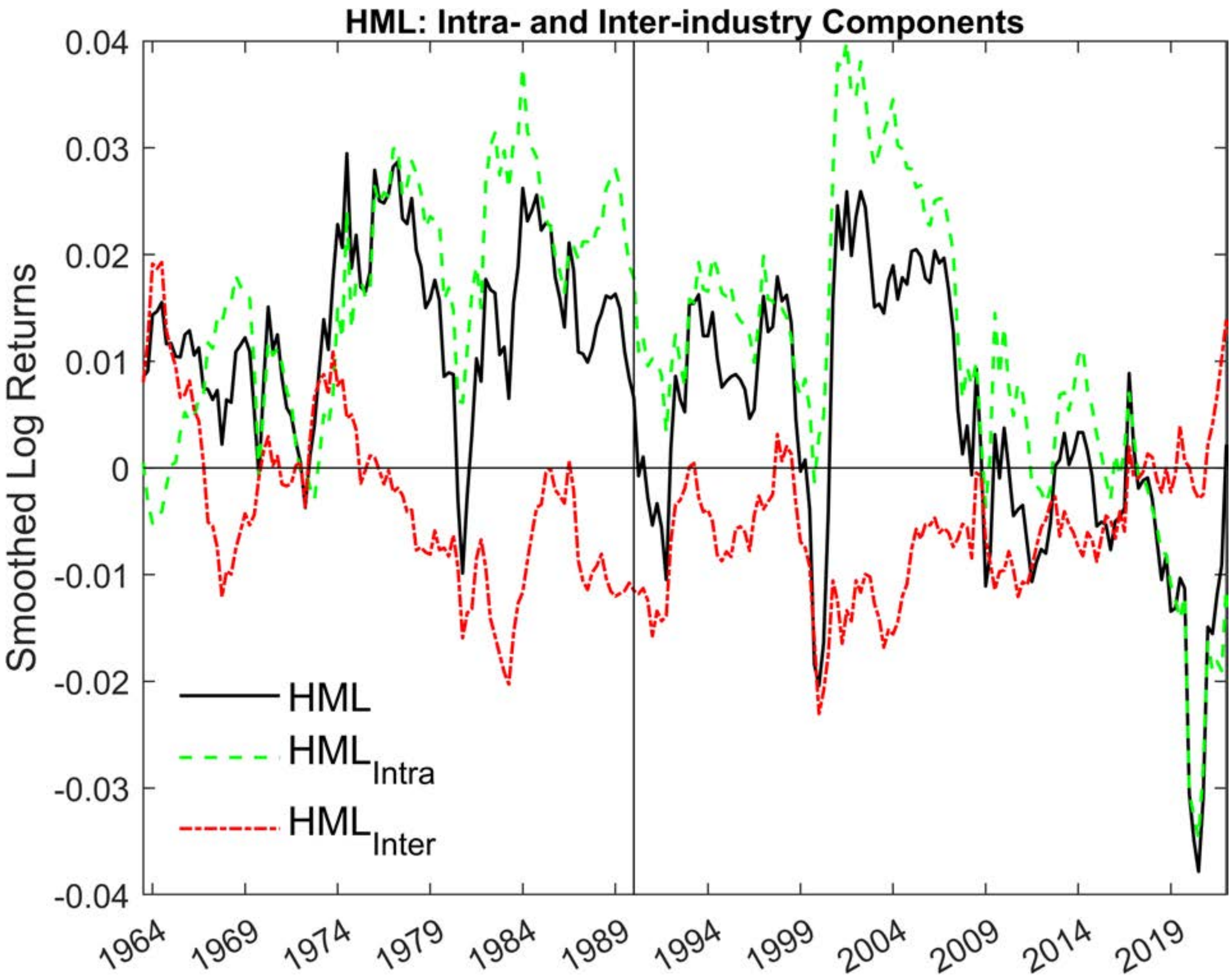

Figure 2: We plot the results from the Table 2 decomposition of HML into its intra- and inter-industry components for the Compustat period from 1963Q3-2022Q1. The solid black line shows the smoothed log return to Fama and French's (1993) HML; the dashed green line shows the smoothed log return to the intra-industry component of HML; and the dashed-dotted red line shows the smoothed log return to the inter-industry component. The series are smoothed with a trailing exponentially weighted moving average in which the decay parameter is set to 0.08 per quarter, and the smoothed series is generated, for example, as $MA_t(\text{HML}) = 0.08\text{HML}_\text{t} + (1\text{-}0.08)MA_{t-1}(\text{HML})$. This decay parameter implies a half-life of two years. The vertical line indicates the start of the subperiod 1990Q2-2022Q1.

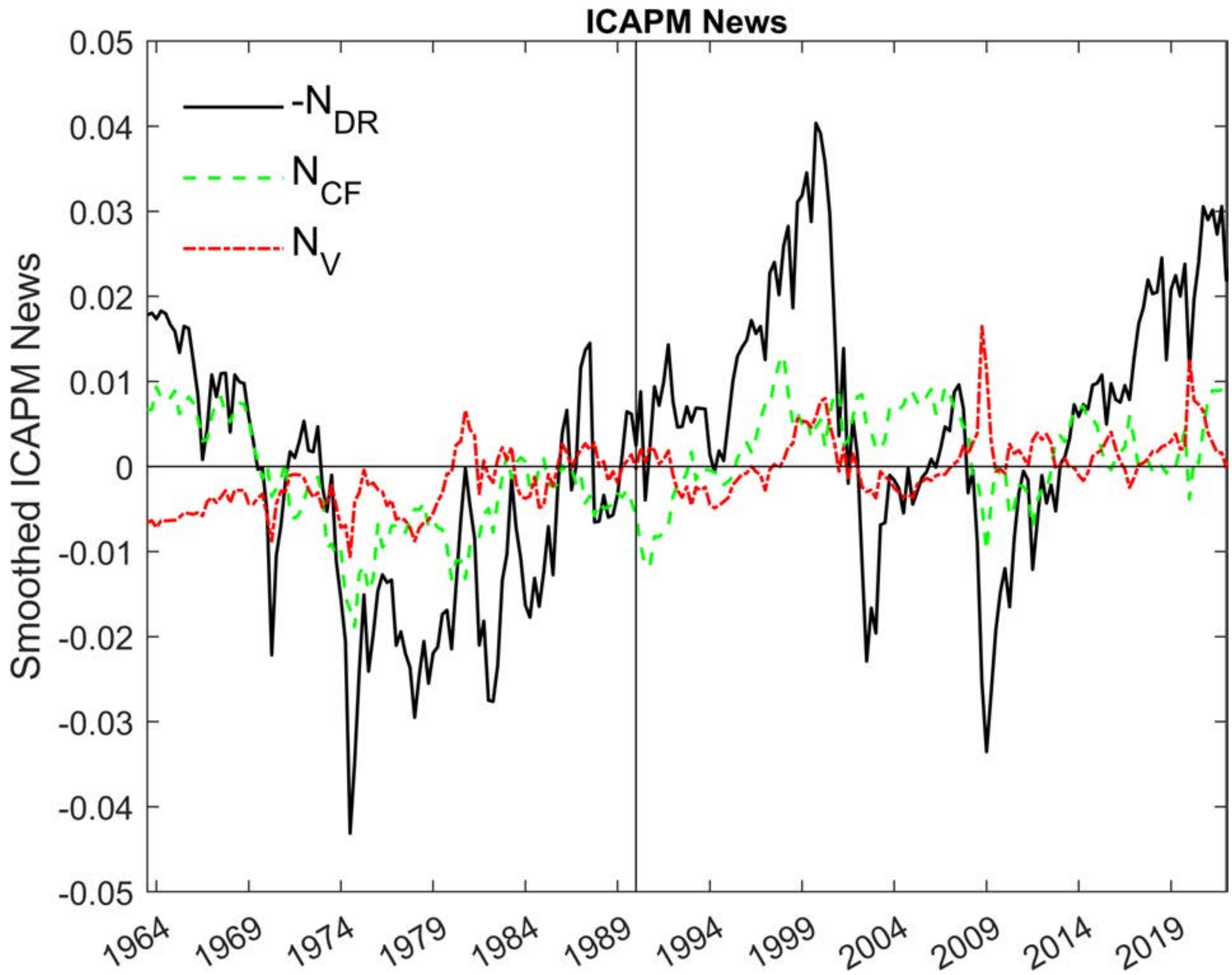

Figure 3: We plot smoothed ICAPM News for the Compustat subsample from 1963Q3-2022Q1 as generated by the VAR in Appendix Table 1. The solid black line shows the negative of smoothed aggregate discount-rate news; the dashed green line shows smoothed aggregate cash-flow news; and the dashed-dotted red line shows smoothed aggregate variance news. The series are smoothed with a trailing exponentially weighted moving average in which the decay parameter is set to 0.08 per quarter, and the smoothed series is generated, for example, as $MA_t(N^{CF}) = 0.08N_t^{CF} + (1\text{-}0.08)MA_{t-1}(N^{CF})$. This decay parameter implies a half-life of two years. The vertical line indicates the start of the subperiod 1990Q2-2022Q1.

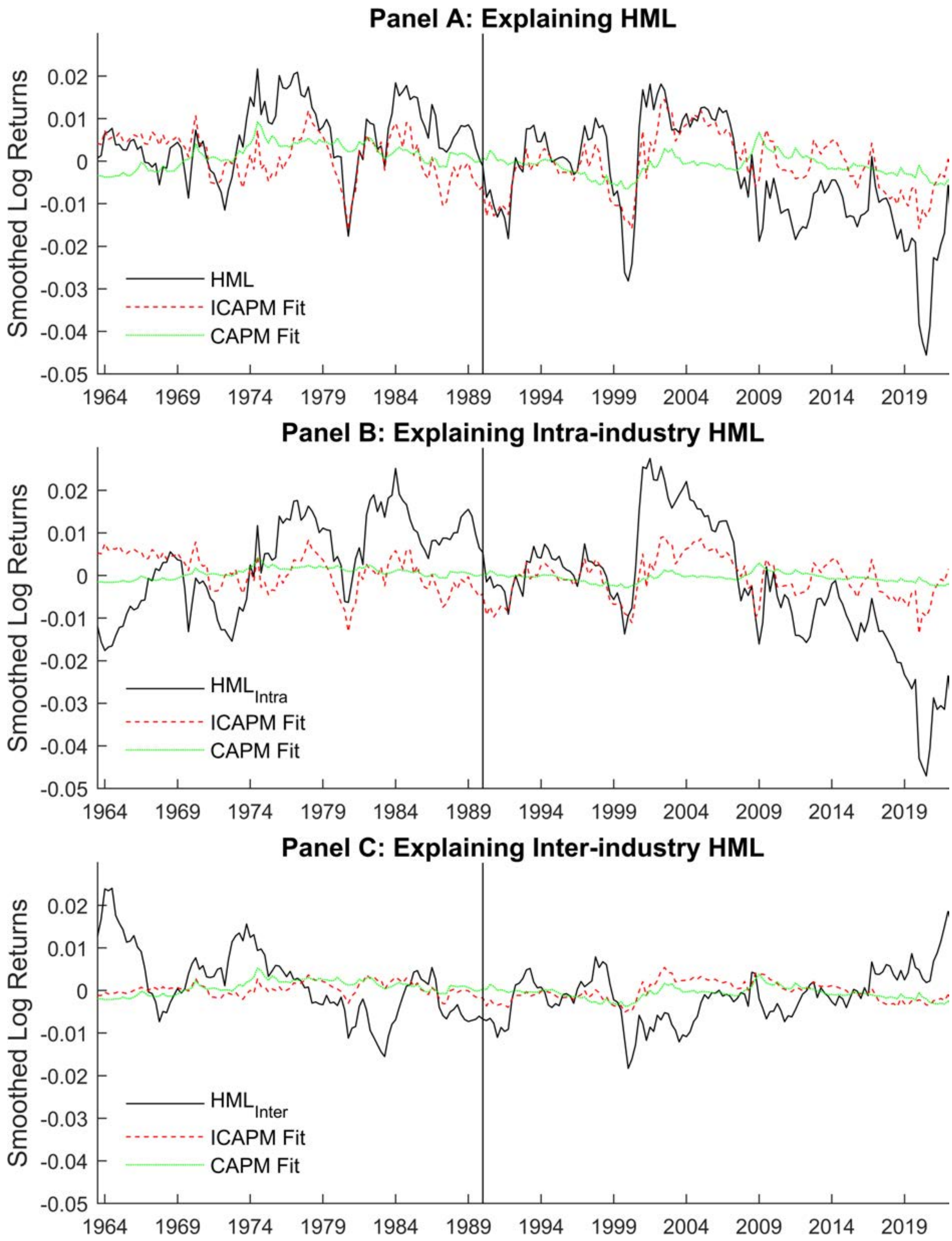

Figure 4: We explain time-series variation in demeaned HML, HML_{Intra}, and HML_{Inter}. Smoothed log returns are plotted with a solid black line while smoothed ICAPM (CAPM) fitted values are plotted with a dashed red (dotted green) line.

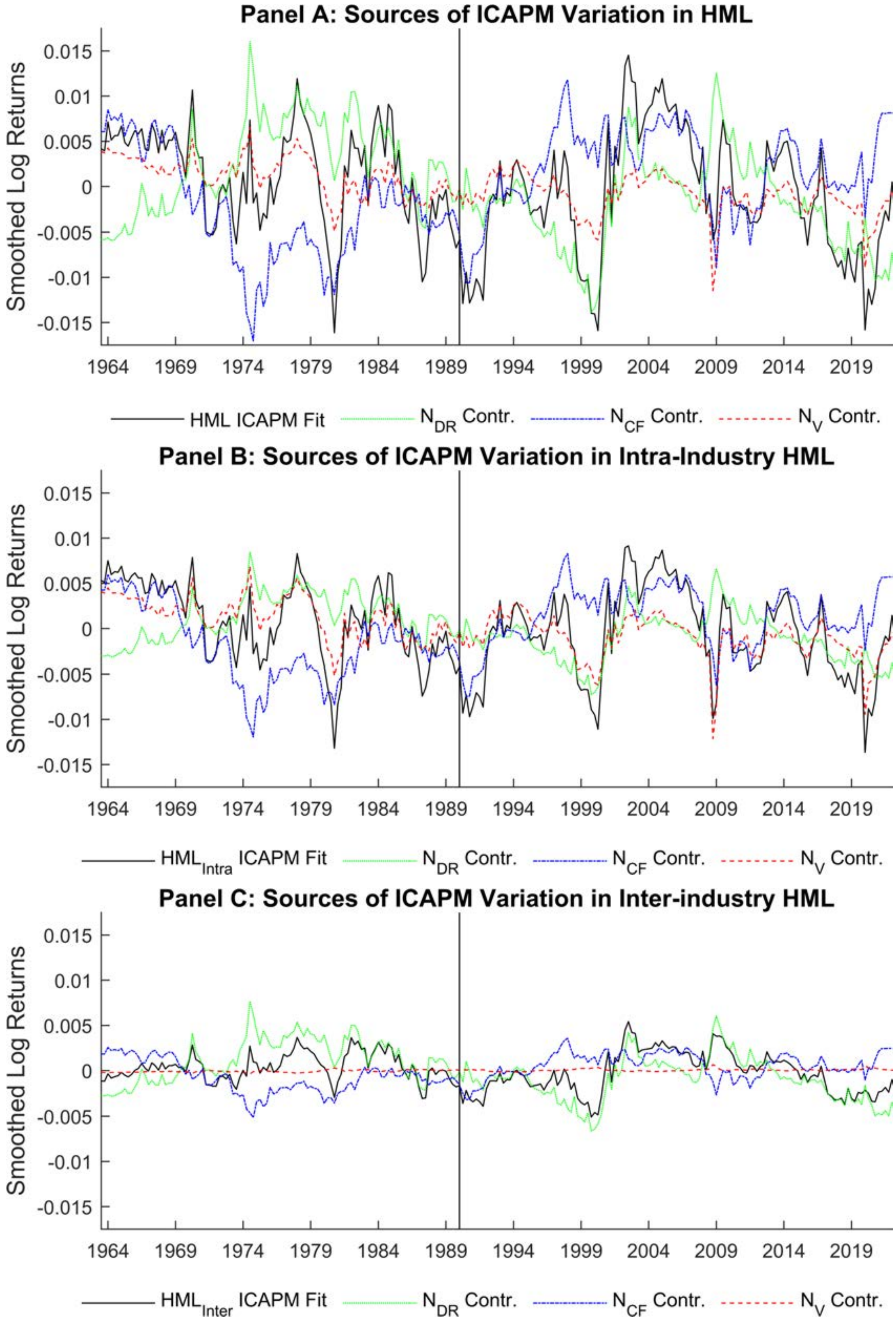

Figure 5: We plot the components of the ICAPM fit for HML, HML_{Intra}, and HML_{Inter}. The solid black line shows the smoothed ICAPM fit; the dashed green line shows the smoothed contribution of N_{DR}; the dashed blue line shows the smoothed contribution of N_{CF}; and the dashed red line shows the smoothed contribution of N_V.

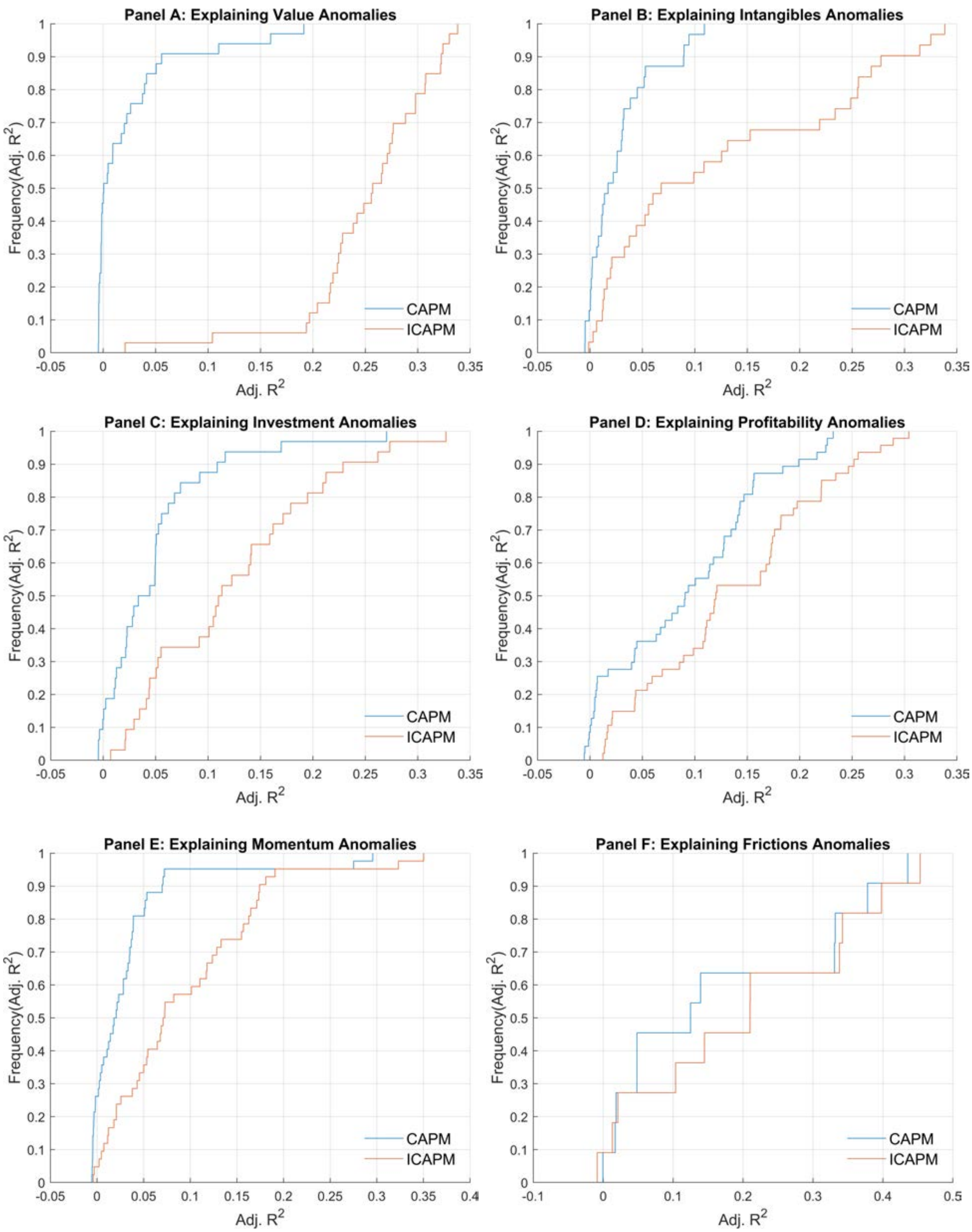

Figure 6: We explain the returns on the six subsets of anomalies replicated by Hou, Xue, and Zhang (2020) for the 1967Q1-2022Q1 period, plotting the resulting cdfs describing the R^2s distributions for the CAPM (blue line) and the ICAPM (red line).

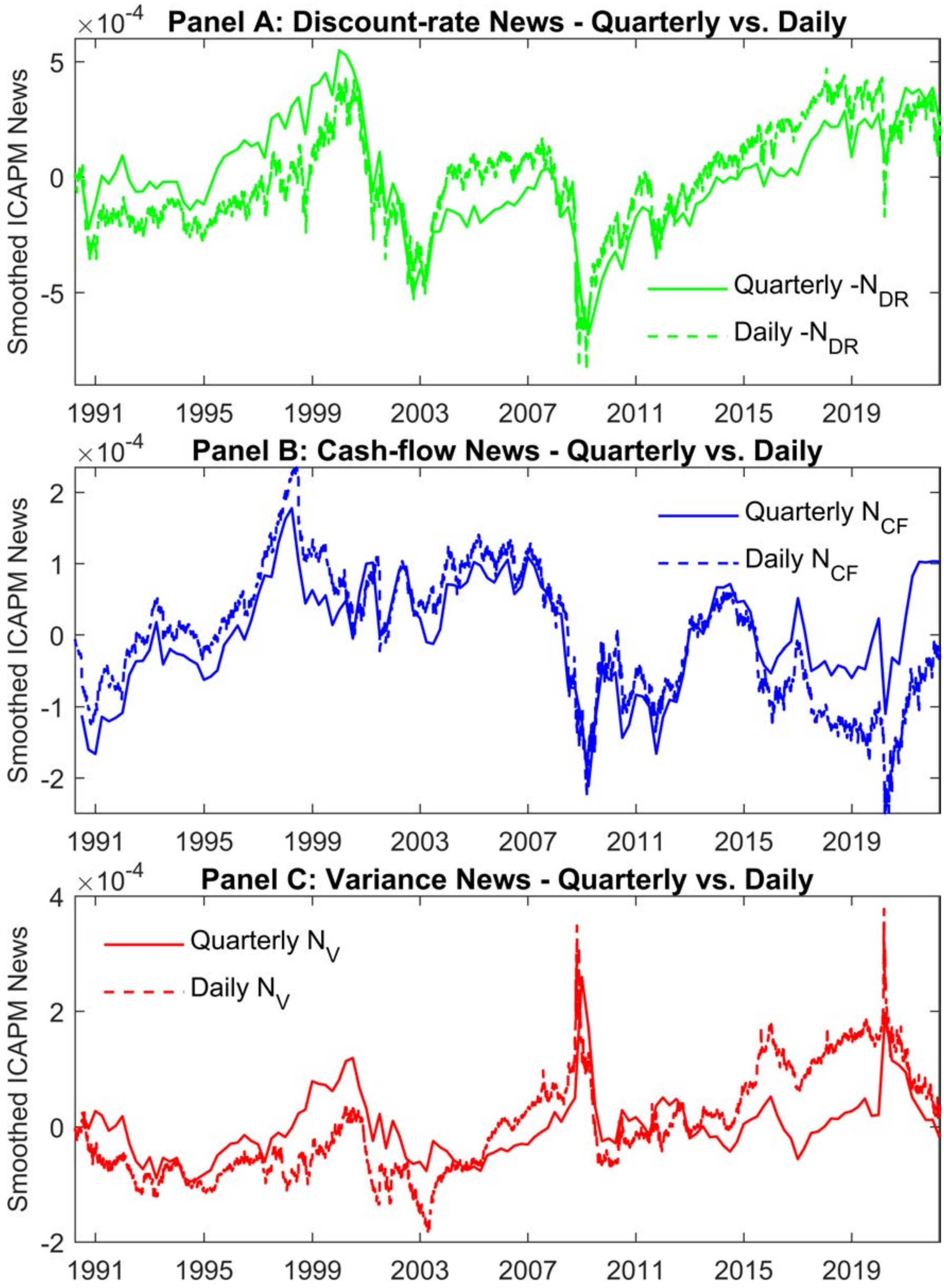

Figure 7: We plot smoothed ICAPM News for the 1990-04-02 to 2022-03-31 subsample as generated by the quarterly VAR in Appendix Table 1 and daily VAR in Appendix Table 2. The solid (dashed) green line shows the negative of smoothed quarterly (daily) $\mathrm{N_{DR}}$; the solid (dashed) blue line shows accumulated quarterly (daily) $\mathrm{N_{CF}}$; and the solid (dashed) red line shows accumulated quarterly (daily) $\mathrm{N_V}$.

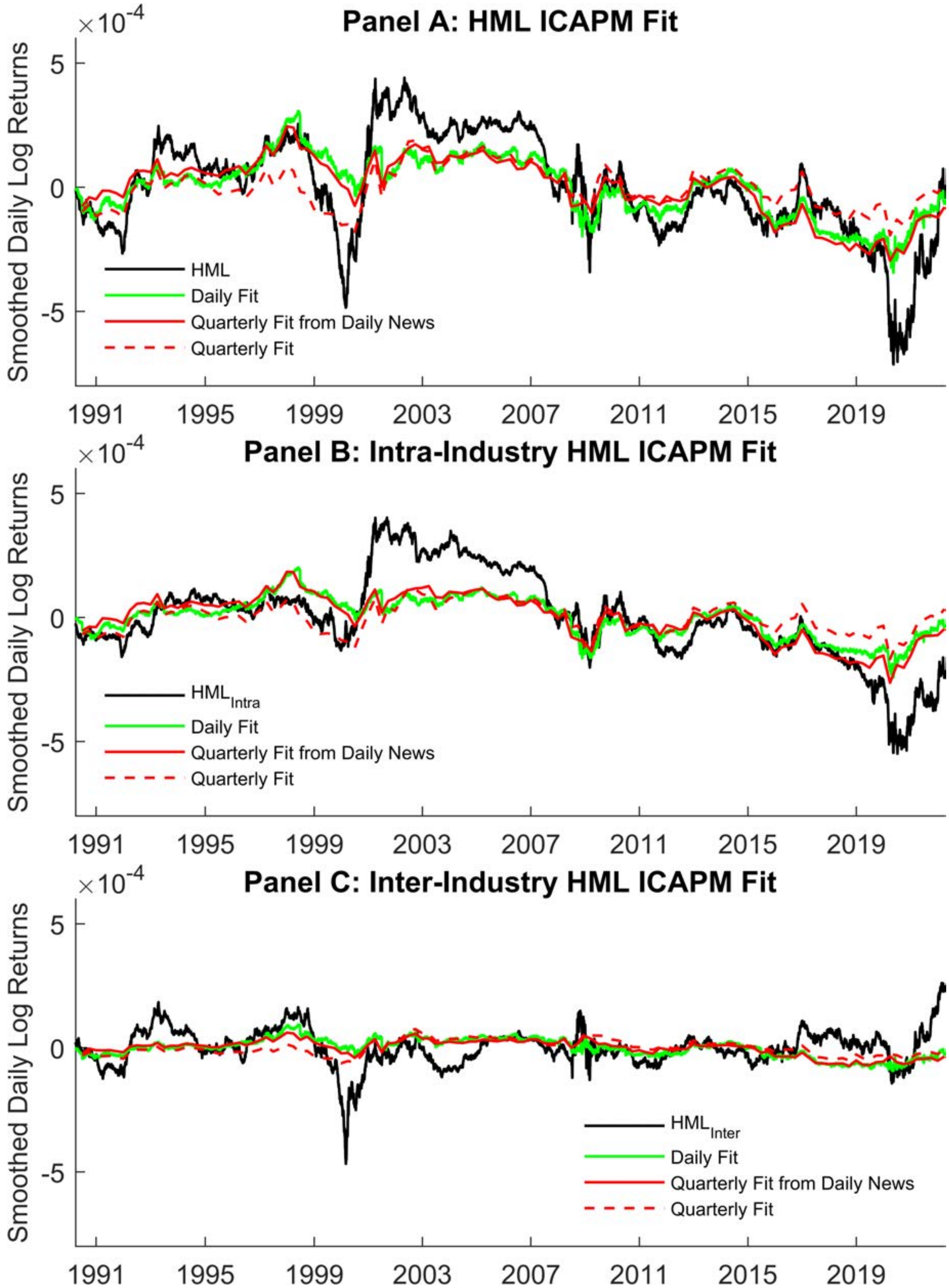

Figure 8: We plot smoothed ICAPM Fits for HML, HML_{Intra}, and HML_{Inter} over the 1990-04-02 to 2022-03-31 subsample as generated by the quarterly VAR in Appendix Table 1 and daily VAR in Appendix Table 2.

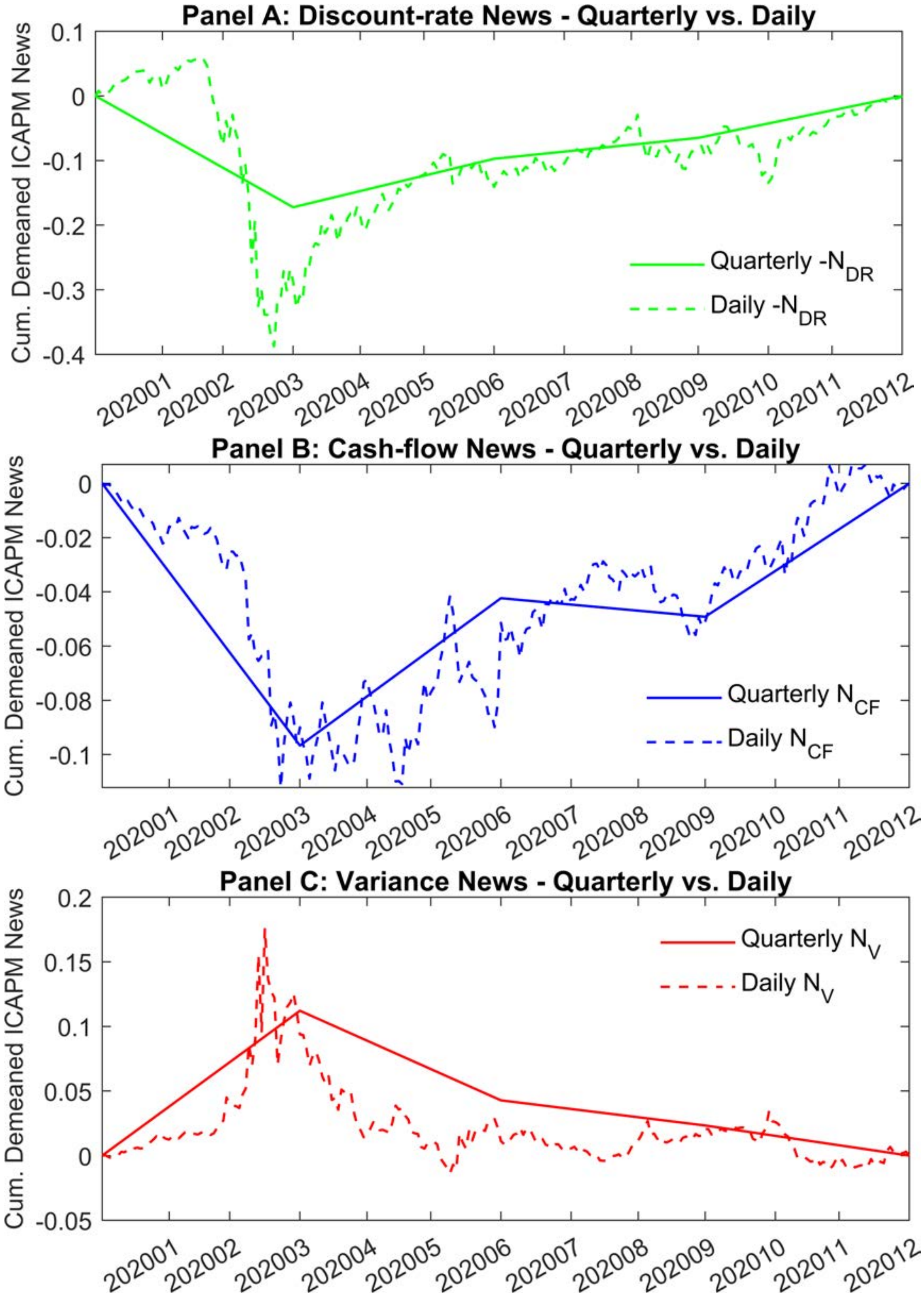

Figure 9: We plot cumulative ICAPM News for the 2020-01-02 to 2020-12-31 subsample as generated by the quarterly VAR in Appendix Table 1 and daily VAR in Appendix Table X. The solid (dashed) green line shows the negative of accumulated quarterly (daily) N_{DR}; the solid (dashed) blue line shows accumulated quarterly (daily) N_{CF}; and the solid (dashed) red line shows accumulated quarterly (daily) N_V.

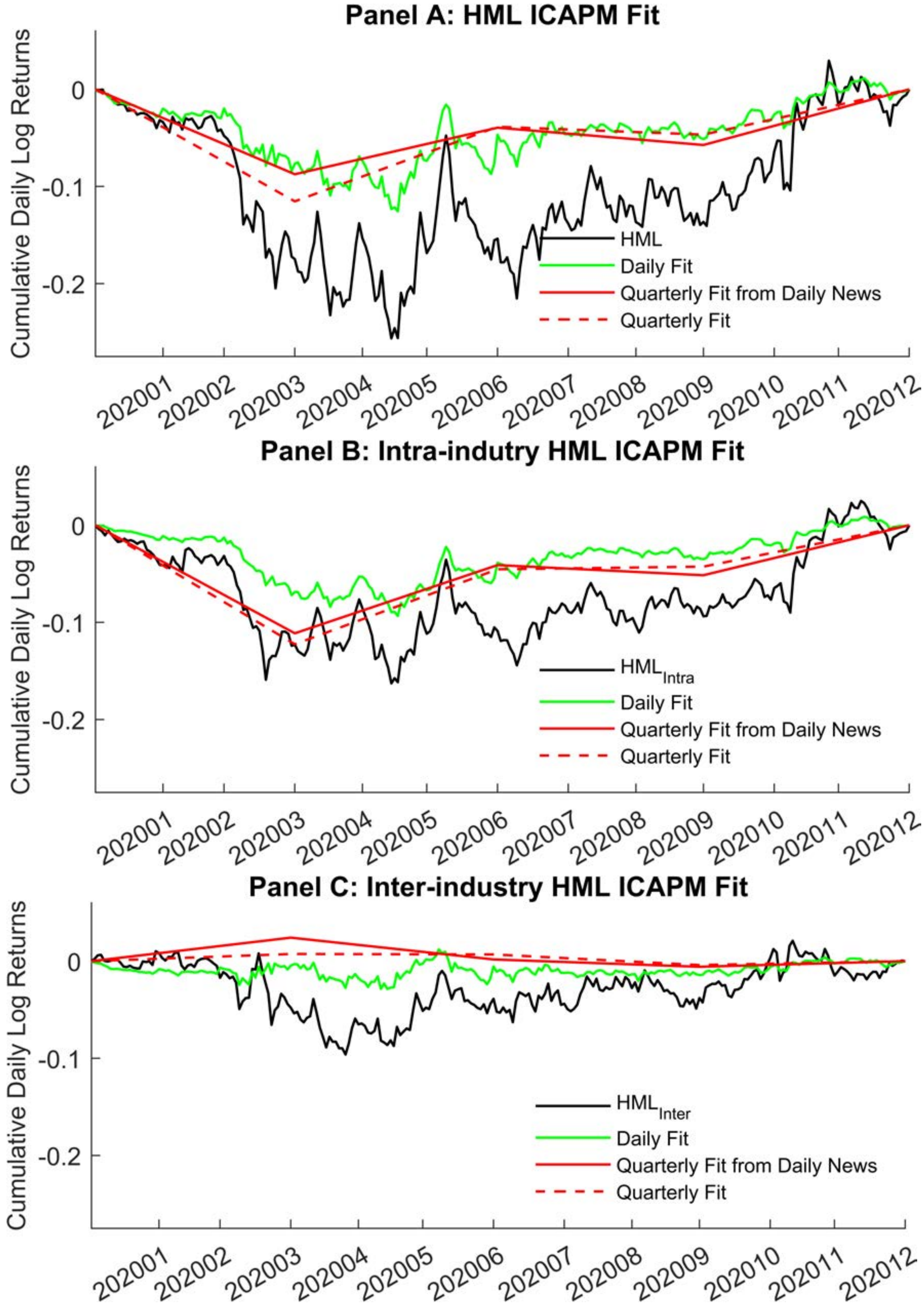

Figure 10: We plot various cumulative ICAPM fits for HML, HML_{Intra}, and HML_{Inter} from the quarterly and daily VARs for the 2020-01-02 to 2020-12-31 subsample.

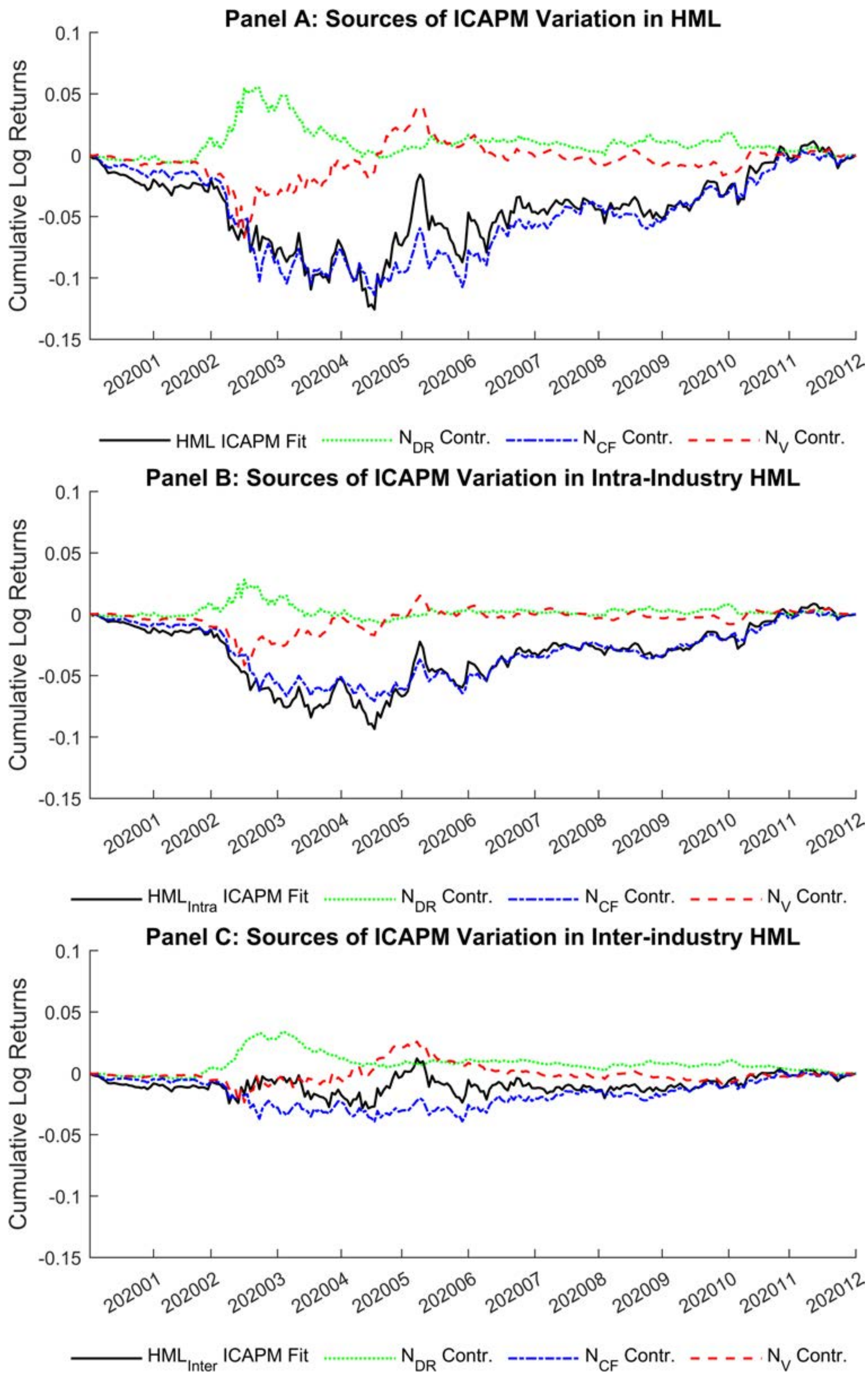

Figure 11: We plot the components of the ICAPM fit for HML, $\mathrm{HML_{Intra}}$, and $\mathrm{HML_{Inter}}$ for the 2020-01-02 to 2020-12-31 subsample. The solid black line shows the smoothed ICAPM fit; the dashed green line shows the smoothed contribution of $\mathrm{N_{DR}}$; the dashed blue line shows the smoothed contribution of $\mathrm{N_{CF}}$; and the dashed red line shows the smoothed contribution of $\mathrm{N_V}$.

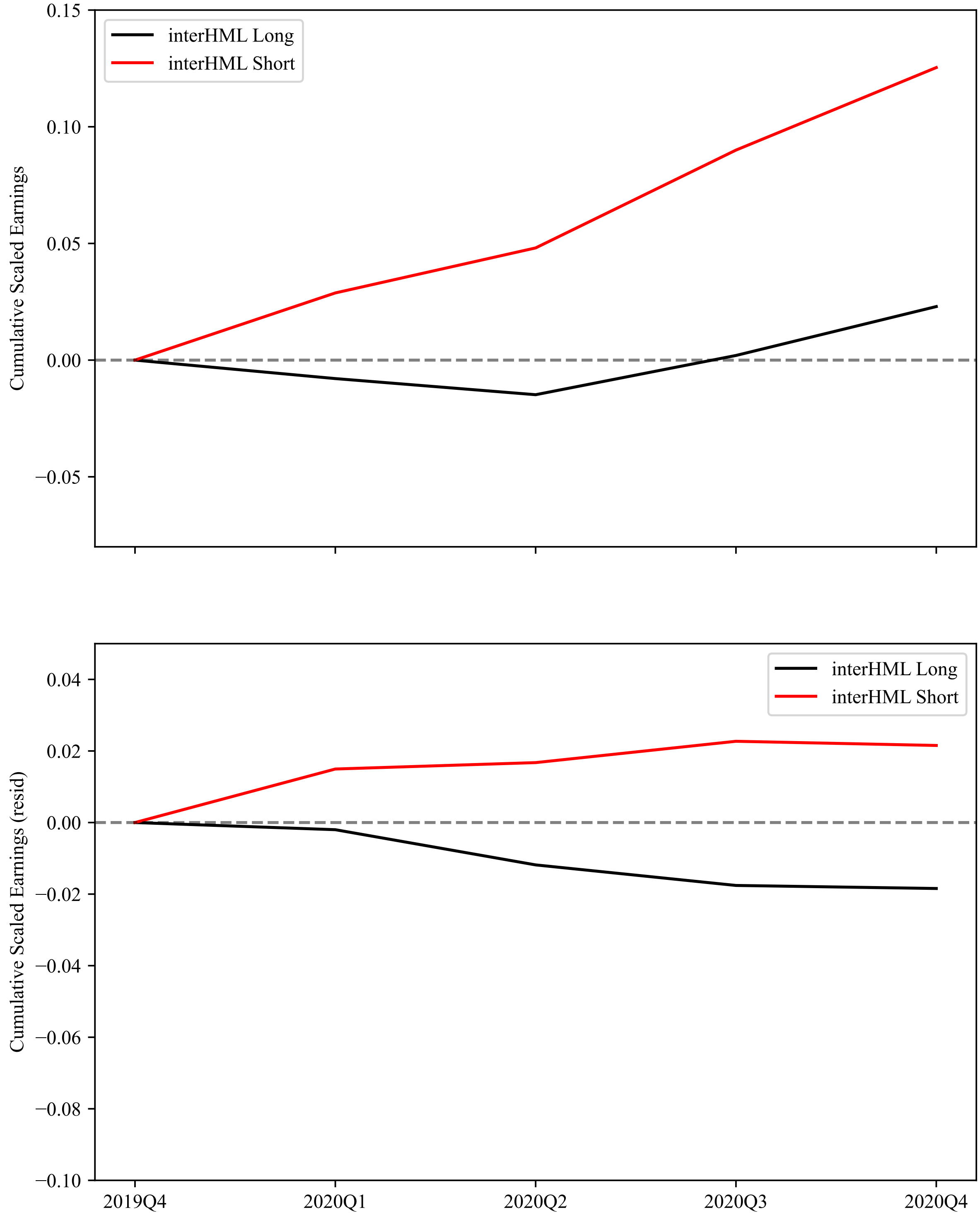

Figure 12: This figure shows the cumulative earnings during 2020 (scaled by total book equity in 2019q4, $ScaledCumulEarn^{p}_{t,t+h}$) for the long side (black line) and short side (red line) of the inter-industry HML portfolio. The bottom panel shows the residuals in 2020 from a regression of the scaled cumulative earnings at each horizon onto the equivalent for the market, to account for the portfolios' earnings' exposures to aggregate earnings.

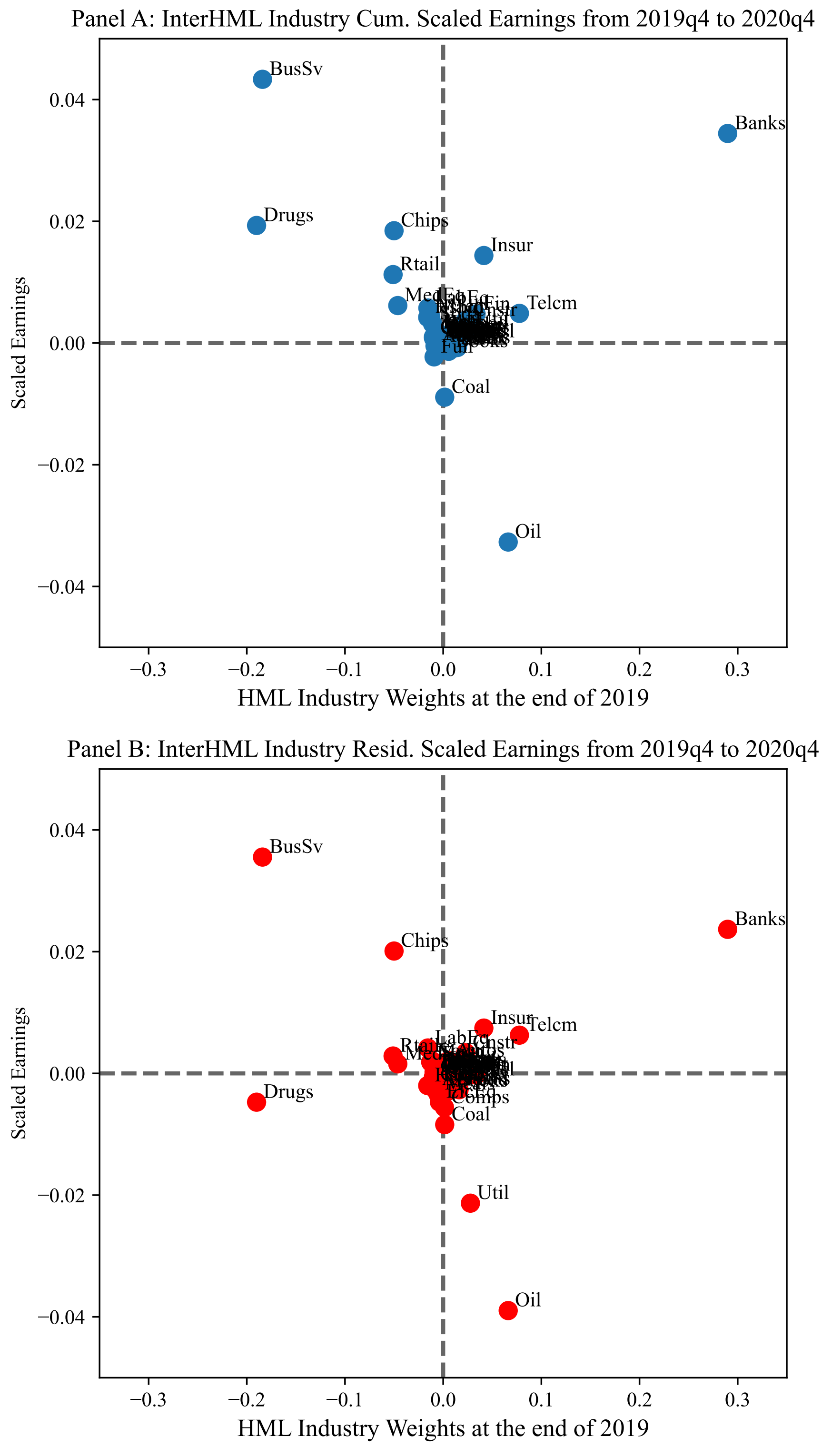

Figure 13: The top panel of the figure reports HML's weights in each industry at the end of 2019 on the X axis and that industry's contribution to HML's cumulative earnings in 2020 on the Y axis. The bottom panel repeats the exercise after residualizing the earnings to the aggregate ones.